HYDROLOGY AND WATER QUALITY MODELLING:

Applying the Soil Water Assessment Tool at 5th Canadian Division Support Base Gagetown

MODÉLISATION HYDROLOGIQUE ET DE LA QUALITÉ DE L'EAU:

Mise en application de l'outil d'évaluation du sol et de l'eau SWAT à la Base de soutien de la 5e Division du Canada Gagetown

A Thesis Submitted to the Division of Graduate Studies

of the Royal Military College of Canada

by

Shawn Matthew Burdett

Captain

In Partial Fulfillment of the Requirements for the Degree of

Masters of Applied Science

April, 2014

Acknowledgements

There were numerous organizations that provided critical data and support for this research. I would like to extend my gratitude to the Department of Fisheries and Ocean personnel, who collected most of the hydrographic and water quality data, and the Joint Meteorological Section in Gagetown, who collected all climate data utilized in this study. Thanks are also extended to the Geocell at 5 CDSB Gagetown for providing GIS data. The Environmental Science Group at the Royal Military College of Canada also provided valuable logistical support and guidance throughout this research. The Environmental Section at 5 CDSB Gagetown contributed to the initiation of this research, in support of their Sediment and Erosion Control Plan. They also provided valuable information, support and guidance throughout this study. Lastly, I would like to extend my gratitude to my supervisor, Dr. Michael Hulley. His knowledge and consultation was a highly valued aspect of this research project.

The contents of this research were presented at the Canadian Association of Water Quality 28th Eastern Symposium in Kingston, Ontario. This presentation was awarded the Philips H. Jones award and was accompanied by an invitation to submit an article to the Water Quality Research Journal of Canada. This article, included in Appendix I, has been submitted to this organization and is pending review and publication. Thanks are given to the co-authors of this article and those who contributed to its review.

Abstract

A hydrological and water quality model is sought to establish an approach to land management decisions for a Canadian Army training base. Training areas are subjected to high levels of persistent activity creating unique land cover and land-use disturbances. Deforestation, complex road networks, off-road manoeuvres, and vehicle stream-crossings are among major anthropogenic activities observed to affect these landscapes. Expanding, preserving and improving the quality of these areas to host training activities for future generations is critical to maintain operational effectiveness. Inclusive to this objective is minimizing resultant environmental degradation, principally in the form of hydrologic fluctuations, excess erosion, and sedimentation of aquatic environments. In some situations these impacts (particularly sedimentation) could be considered a violation of environmental legislation, such as the *Fisheries Act*. Application of the Soil Water Assessment Tool (SWAT) was assessed for its ability to simulate hydrologic and water quality conditions observed in military landscapes at 5th Canadian Division Support Base (5 CDSB) Gagetown, New Brunswick. Despite some limitations, this model adequately simulated three partial years of daily watershed outflow (NSE = 0.47-0.79, R^2 = 0.50-0.88) and adequately predicted suspended sediment yields during the observation period (%d = -47 to 44%) for one highly disturbed sub-watershed in Gagetown. Further development of this model may help guide decisions to develop or decommission training areas, guide land management practices and prioritize select landscape mitigation efforts.

Résumé

On cherche à mettre au point un modèle hydrologique et de la qualité de l'eau afin d'établir une démarche de prise de décisions en matière de gestion des terres d'une base d'instruction de l'Armée canadienne. Les secteurs d'entraînement des bases sont le théâtre d'activités intensives et soutenues, qui sont à l'origine de perturbations particulières sur le plan de la couverture et de l'utilisation des terres. La déforestation, la création de réseaux routiers complexes, les manœuvres hors route et la traversée de cours d'eau par des véhicules figurent parmi les principales activités anthropiques observées ayant des incidences sur les écopaysages de ces secteurs. L'expansion, la préservation et l'amélioration de la qualité de ces secteurs pour que les générations futures puissent aussi y mener leurs activités d'entraînement sont essentielles au maintien de l'efficacité opérationnelle. Il s'agit également de réduire au minimum la détérioration de l'environnement découlant de ces activités, principalement les fluctuations hydrologiques, l'érosion excessive et la sédimentation des milieux aquatiques. Dans certaines situations, de telles répercussions (en particulier la sédimentation) pourraient être considérées comme une violation de lois environnementales comme la *Loi sur les pêches*. On a procédé à une étude sur la capacité de l'outil d'évaluation du sol et de l'eau SWAT à simuler les conditions hydrologiques et de qualité de l'eau observées dans les écopaysages militaires à la Base de soutien de la 5^e^ Division du Canada Gagetown, au Nouveau-Brunswick. Malgré quelques limites, le modèle a efficacement simulé le débit quotidien à l'exutoire d'un bassin hydrographique sur trois années partielles (ENS = 0,47-0,79; R^2 = 0,50-0,88). L'outil a également bien prédit l'apport de sédiments en suspension pour la période d'observation (% d = -47-44 %) pour un sous-bassin hydrographique de Gagetown ayant subi des perturbations importantes. Le perfectionnement de ce modèle pourrait aider à aiguiller les décisions quant au développement ou à la mise hors service des secteurs d'entraînement, à orienter les pratiques en matière de gestion des terres, et à cibler les efforts de réduction des dommages causés aux écopaysages.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AAFC	Agriculture and Agri-Food Canada
BARR	Barren Land Cover (Including Roads and Tracks)
BMP	Best Management Practice
CCME	Canadian Council of Ministers of the Environment
CEQG	Canadian Environmental Quality Guidelines
CN	Curve Number (SCS CN)
CUP	Calibration and Uncertainty Program
DEM	Digital Elevation Model
DFO	Department of Fisheries and Oceans Canada
DHSVM	Distributed Soil Vegetation Model
FRST	Mixed-Forest Land Cover
GIS	Geographic Information System
GLUE	Generalized Likelihood Uncertainty Estimation
HEM	Hillslope Erosion Model
HRU	Hydrological Response Unit
HSPF	Hydrological Simulations Program – Fortran
IPS	Ideal Performance Standards
IQR	Inter-Quartile Range
LAI	Leaf Area Index
LID	Low Impact Development
LISEM	Limburg Soil Erosion Model
LULC	Land-Use and Land Cover
(M/R)USLE	(Modified or Revised) Universal Soil Loss Equation
NAESI	National Agri-Environmental Standards Initiative
NPS	Non-Point Source (Pollution)
(P)ET	(Potential) Evapotranspiration
PGSL	Parleeville Gravelly Sandy Loam
SGSL	Sunbury Gravelly Sandy Loam
RNGB	Brush Land Cover
RNGE	Grassland Land Cover
RTA	Range and Training Area (in Base Gagetown)
SEV	Severity of Ill Effects
SCS	Soil Conservation Service
MLR	Multiple Linear Regression
SUFI2	Sequential Uncertainty Fitting
SWAT	Soil Water Assessment Tool
TDML	Total Daily Maximum Load
TRCL	Tracy Loam
TSS	Total Suspended Solids
US	United States of America
USDA	United States Department of Agriculture
USLE	Universal Soil Loss Equation
USPED	Unit Stream Power Erosion Deposition
VSA	Variable Source Area
WAM	Wet Area Mapping
WEPP	Water Erosion Prediction Project
WQI	Water Quality Index
1(2/3)-D	One Dimensional (Two or Three Dimensional)
5 CDSB	5th Canadian Division Support Base

Nomenclature

a	Baseflow Filter Recession Parameter
BFI_{max}	Baseflow Filter for Long Term Ratio of Total Baseflow Parameter
b_t	Baseflow at Time t (m^3 s^{-1})
C	USLE Cover Factor
$c_{soilstr}$	Soil Structure Class
c_{perm}	Soil Permeability Class
i	Observation Number
K	USLE Erodibility Factor (0.013 tonnes m^2 hr m^{-3} $tonnes^{-1}$ cm^{-1})
m_s	Percent Sand Content
m_{silt}	Percent Silt Content
m_{vfs}	Percent Silt Content
n	Number of Observations
NSE	Nash-Sutcliffe Efficiency
OM	Percent Organic Matter
P	USLE Practice Factor
P_f	Discharge Exceedance Probability
P-Factor	Percent of Observations Covered by 95PPU
α	Statistic Confidence Threshold
Q	Discharge (m^3 s^{-1})
Q_m	Measured Discharge (m^3 s^{-1})
Q_s	Simulated Discharge (m^3 s^{-1})
R_{day}	Daily Rainfall Depth (mm)
R^2	Coefficient of Determination
R-Factor	Relative Width Covered by 95 PPU
sed	MUSLE Erosion Rate (tonnes day^{-1})
T	Turbidity (NTU)
t	Metric Tonnes
T_{av}	Mean Daily Air Temperature (°C)
T_{water}	Mean In-Stream Water Temperature (°C)
TSS	Total Suspended Solids (mg L^{-1})
t-Stat	Statistic t-Distribution Percentage Points
%d	Percent Difference

*Additional SWAT parameters defined in Appendix A

1 Introduction

1.1 Background

5 CDSB Gagetown is located in Southern New Brunswick and is one of the largest military training facilities in Canada, covering an area of over 1,100 km^2 (Figure 1). The Range and Training Area (RTA) in Gagetown host Army operations for approximately 98,000 personnel training-days each year, including 800 heavily armored track vehicle and 14,000 wheeled vehicle training-days. Included in the RTA are 21,000 ha of manoeuvre fields, 30,000 ha of ranges and impact areas, 829 km of roads, 362 km of off-road trails, more than 500 fords and 1,174 in-stream culverts and bridges. Primary land cover categories can be described as forested (66%), grasslands and early succession (18%), aquatic environments (10%) and barren areas (6%). Generally, grasslands are highly disturbed from off-road vehicle manoeuvres and include dense track networks. Barren areas include roads, recently devegetated areas being converted to grasslands and areas that are persistently barren due to repetitive vehicle traffic. Extensive vegetation management (e.g. cutting, spraying or burning) and army training activities are among a variety of activities observed to significantly impact these landscapes.

The base was established in the 1950's, which involved the expropriation of private lands including several communities, agricultural areas and forest harvest blocks. Additional land was deforested to create the manoeuvre fields, ranges and munition impact areas at this time. In the 1990's another 7,000 ha of forests were cleared in an attempt to create more manoeuvre areas; however, many of these areas were not used for years because of erosion and vegetation issues.

Aquatic environments within the Gagetown RTA include 3,272 km of watercourses, 156 lakes and ponds, and 6,487 ha of wetlands. Poor water quality, suspended solids in particular, has been recorded throughout the area (Hood, 2013), along with potential stress to some benthic communities (Estrada et al., 2012). Increased surface runoff, decreased baseflow, elevated erosion rates, increased sediment yields and increased stresses to aquatic environments have been identified as watershed management issues at 5 CDSB Gagetown. Atlantic salmon and brook trout are primary fish species of management interest (Smith, 2014). At this time, the base is undertaking a multi-year, multi-million dollar project to address some of these issues under the Sediment and Erosion Control Plan.

1.2 Problem Definition

Land managers at Gagetown have limited quantitative understanding of watershed processes and how they are affected by the diverse and unique conditions observed on Army training grounds. The scale of this area and the ability to affect significant change across the landscape instil significant cause to objectively manage detrimental impacts to the hydrological and sediment cycle. At this time, there are limited considerations behind the allocation of resources used to manage these lands due to the lack of understanding and availability of practical management tools for these unique landscapes. An approach, tool and/or method that could be used to objectively design landscape alterations, guide training or management operations and prioritize mitigation efforts would be extremely valuable to help achieve operational and environmental goals while optimizing available resources.

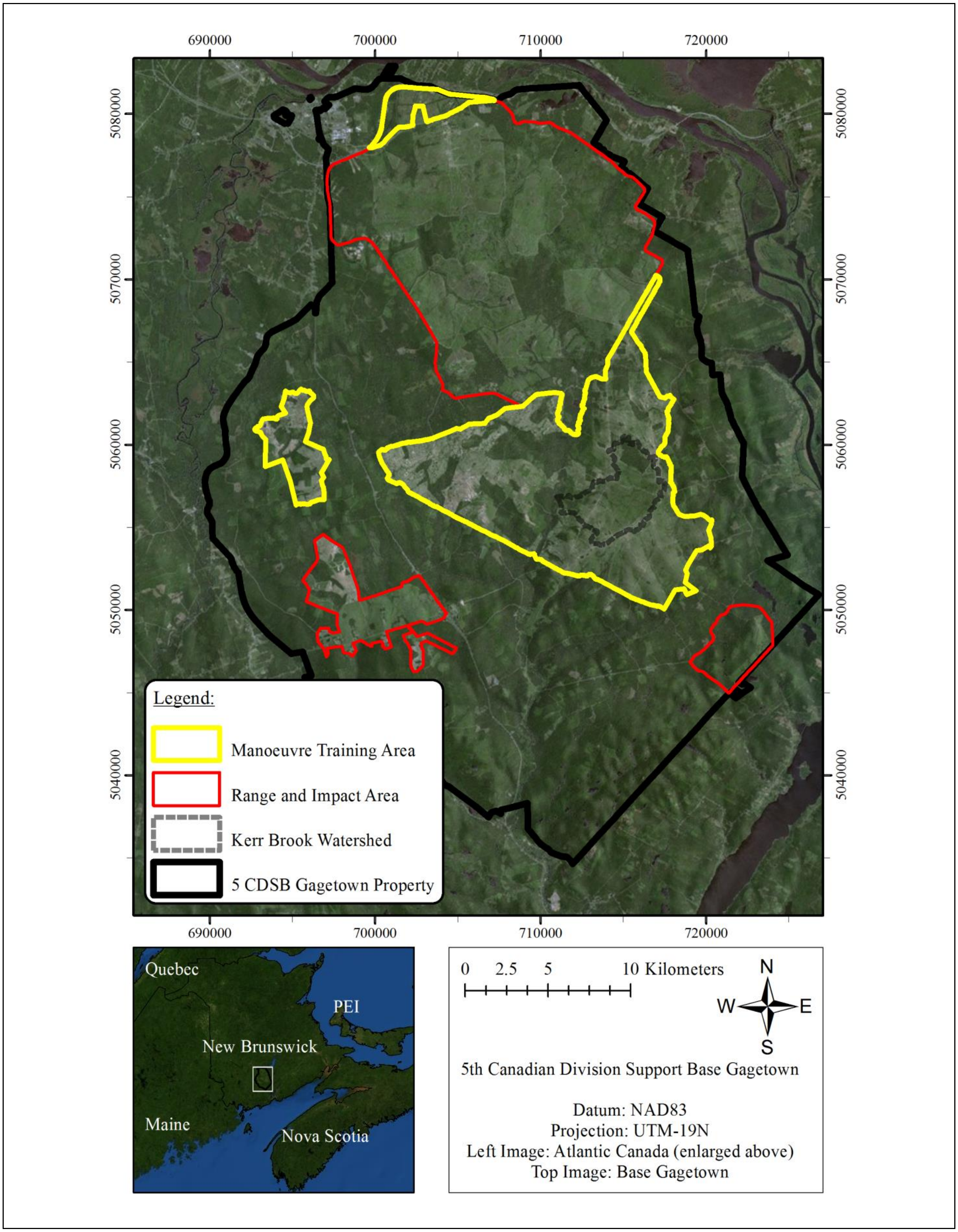


Figure 1. Atlantic Canada, Gagetown and the Kerr Brook watershed.

1.3 Objectives

Effective watershed management is an extremely challenging task, particularly for areas that are poorly understood, such as military training grounds. Hydrological and water quality modelling tools are becoming an increasingly popular means to address complex watershed management issues. However, standing alone, these models may be of limited value unless applied within a defined management strategy and holistic context. For these reason there were three primary objectives of this study:

1) The first objective was to perform a review of watershed modelling tools and management approaches, with a focus on military training grounds. This was designed as a resource for professionals involved with the management of similar lands within Canada. It will provide insight into different fields within watershed management, different modelling approaches and alternative avenues for further research. This also included collecting and compiling data to develop a database relevant to this field of research;
2) The second objective was to assess a watershed modelling tool for its ability to predict hydrologic and water quality conditions associated with generic military landscapes. This was accompanied by a critical sensitivity analysis, calibration exercise and result validation. This was aimed to provide a foundation for additional watershed modelling and management studies, assessment of model limitations and result uncertainties; and
3) The third and final objective of this study was to provide recommendations for continued academic research and military land managers, based on knowledge and findings from the first two objectives. This objective addresses areas requiring refinement for further modelling efforts. Recommendations for alternative study avenues are discussed within different fields to address watershed processes that are suspected to be significant and excluded from the scope of this study.

1.4 Methodology

This research approach involved a literature review concurrent to a critical assessment of available data within the study area. A field study was conducted to provide a sense of watershed conditions and collect necessary supplemental information including soil, stream flow and water quality data. This was followed by the selection of a suitable numerical tool used to simulate hydrological, erosion and water quality conditions. The model was primarily developed from readily available information and passed through a critical sensitivity, calibration and validation procedure. This included uncertainty assessment and evaluation of model limitations. This work provides a foundation for subsequent investigation that will focus on expansion of the simulation period and area, reduction of input parameter uncertainties, improvements to modelling processes and evaluation of mitigation measures. Recommendations regarding related fields of study and management strategies were also discussed.

1.5 Scope

This study focused on a detailed data assessment and model development for the Kerr Brook watershed within the RTA of 5 CDSB Gagetown. This watershed was selected because it is centrally located in the base and within the mounted manoeuvre area. The watershed is highly disturbed, regularly used for military training and well documented with meteorological, GIS, hydrometric and water quality data. This enabled a more refined model development, calibration and validation exercise that improved the confidence and accuracy of model parameters and performance. The model was aimed to operate on a continuous time-step, and integrated all major elements of the hydrological cycle in order to predict total water balance. It was semi-distributed in order to utilize geospatial information to characterize different land-use and land cover (LULC) conditions, how they affect the hydrological cycle and erosion processes.

The complexities of watershed processes limit all models, in one way or another, in their ability to simulate reality. Considering this, and data limitations, several elements were excluded from the scope of this study. Highly distributed sedimentation processes, vegetation parameters, winter hydrology, channel processes and water quality variables (with the exception of suspended sediments and temperature) have limited supporting data and generally demand complex or highly distributed models. These elements were considered throughout this study but to a limited degree and in a qualitative manner only. Available time series data, primarily climate and hydrometric data, governed the simulation time period to enable a proper calibration and validation exercise. To some extent, the available time series information constrained the analysis and limited incorporation of significant changes to the landscape. However, this research provides a starting point that can be improved and refined as additional monitoring information becomes available.

2 Literature Review

This section provides a compilation, though not comprehensive review, of key aspects related to hydrology, river hydraulic, erosion and sedimentation processes. These topics are the technical foundations behind the hydrological and water quality models considered in this research. Advanced topics in some of these fields are mentioned to attribute their value in future modelling and management approaches. The general concept of integrated watershed management is also discussed to provide a context of how numerical models can be integrated into management frameworks. Key literature involving watershed management and modelling for military lands is reviewed to provide a basis for the current state of this topic within other countries, primarily the United States of America (US). Key models applicable to this topic are reviewed and the Soil Water Assessment Tool (SWAT) model is discussed in detail, including case study applications, recent developments and modifications. Water quality guidelines and evaluation methods are discussed to provide potential targets for management strategies. Ecology, fluvial geomorphology, climate change and soil mechanics, to name a few topics, can be very important within integrated watershed management strategies and significantly affect the water and sediment cycle; however, these topics lie outside the scope of this literature review.

2.1 Hydrology

Hydrology is the science in understanding the movement of water through the earth's environment. This movement includes many complex processes, such as precipitation, runoff generation, evapotranspiration, soil water movement, groundwater flow and channel flow. Representing these processes by a simplified system of interactive empirical, conceptual and/or physically-based mathematical equations is the discipline of computerized hydrological modelling (Abbott and Refsgaard, 1996). There are many different methods that aim to conceptualise the hydrological cycle and one method does not stand above the rest. An example of how the SWAT model conceptualises the water cycle is included in Figure 2 (Neitsch et al., 2011).

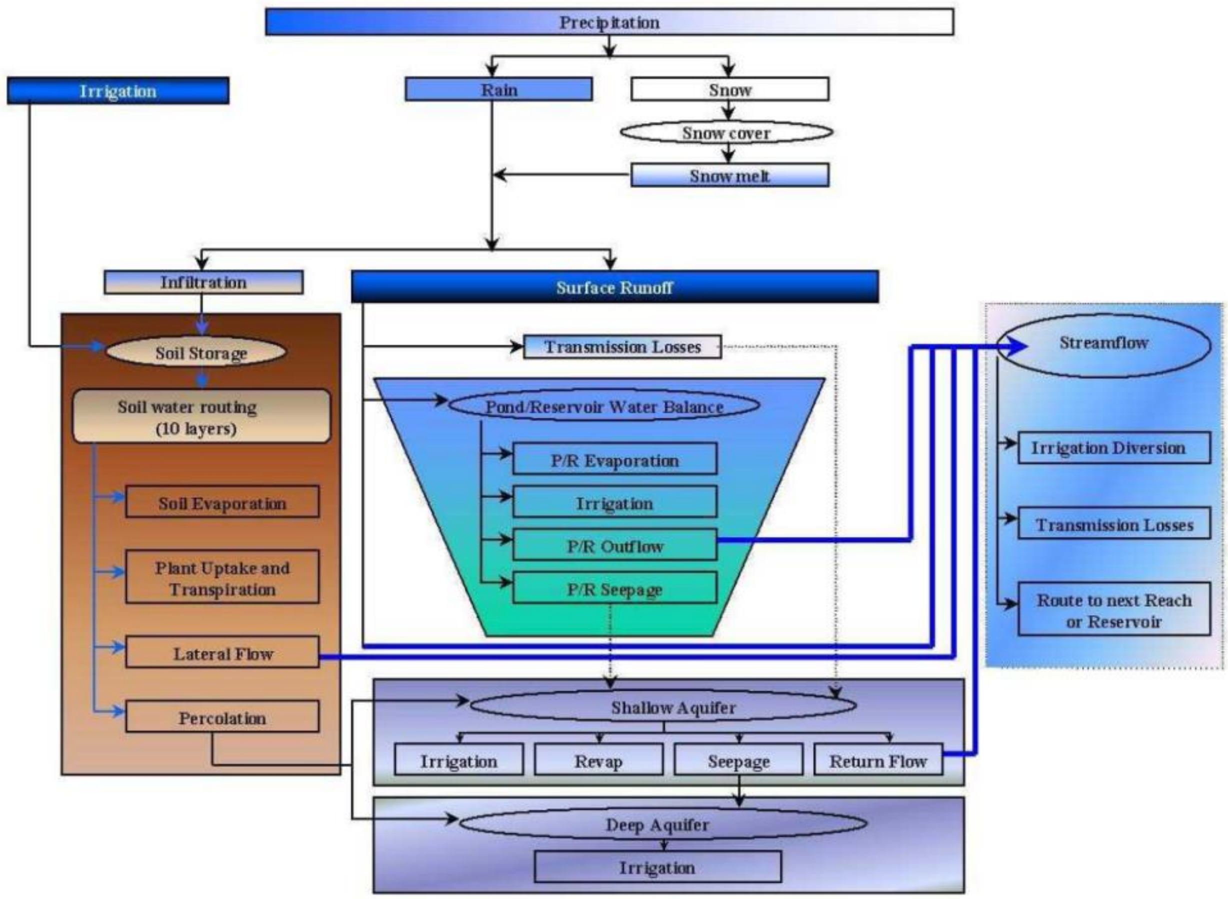


Figure 2. SWAT hydrological conceptual framework.

Hydrological processes can be represented at various spatial and temporal scales. Computational processes can be executed across a watershed by a highly distributed cell mesh, combined into semi-distributed landscape units of relative homogeneity or lumped into large contributing regions, such as the watershed tributaries (Singh, 1995; Abbott and Refsgaard 1996). Water generation and transformation methods can also vary in principle, from empirical frameworks inconsiderate of physical processes, to complex partial-differential equations based on governing physical principles (Abbott and Refsgaard 1996; Todini, 2007). Regardless, all hydrological elements are governed by the conservation of mass, where water entering an element of the hydrological cycle is equal to the change in water stored and water leaving that element. Temporal scales may also vary from minutes to months to model different processes, such as flood wave propagation or seasonal water yields. Ultimately, hydrological model applications and data availability will shape these model characteristics.

Precipitation is the primary driver behind all hydrological processes. Precipitation is generally assigned to watersheds based on their proximity to recording meteorological gauge stations. This assignment can take the form of an arithmetic mean approach, a Thiessen polygon method or an isohyetal approximation, which may account for orographic effects and storm morphology (Bedient and Huber, 1992). Significant uncertainty can be expected in precipitation data due to measurement error and spatial variability, where relative uncertainties of 10% are common (Neitsch et al., 2011). Radar and satellite data are also being increasingly applied to generate precipitation data for hydrological models. These technologies provide the ability to improve spatial and temporal rainfall resolution across a large scale and predict precipitation across poorly gauged areas. However, these technologies require substantial resources, significant quality control and are still susceptible to many sources of error, calling for continued research and development (Kitzmiller et al., 2013).

Surface runoff simulations have evolved from the Rational Method, conceived in the 1850's, to the highly distributed and physically-based models of today (Todini, 2007). During a rainfall of given intensity, surface runoff is usually generated at a rate in excess to the soil's infiltration capacity, after initial abstractions have been filled. Infiltration rates and abstractions can account for soil characteristics, moisture conditions, topography and land cover conditions, such as in the Soil Conservation Service (SCS) Curve Number (CN) method, given in Equation [1] (Neitsch et al., 2011). This equation estimates a daily runoff depth (Q_{surf}, mm) from the daily rainfall depth (R_{day}, mm), the initial abstractions (I_a, mm) and a retention parameter (S, mm). Abstractions and retention are approximated with a CN that is selected based on the hydrological soil group and land cover conditions, which can be adjusted by a slope factor, moisture conditions and/or antecedent climate conditions.

$$Q_{surf} = \frac{\left(R_{day} - I_a\right)^2}{R_{day} - I_a + S} \quad [\ 1\ ]$$

Hortonian overland flow conditions are assumed in many runoff models, where runoff is uniformly generated by excess precipitation and once generated, remains as surface runoff. Another widely supported concept is that surface runoff is dominated by saturated areas, or Variable Source Area (VSA) hydrology (Frankenberger et al., 1999; Todini, 2007; Easton et al., 2008). This runoff is generated in select portions of the landscape and dependent upon soil moisture, leading to variable contributing areas. Rain falling on unsaturated soils generally infiltrate into the ground and only contributes to runoff when the upper soil layer is saturated. This phenomenon is recognized to have significant influence in humid regions, rural areas, well vegetated landscapes and shallow soils (Easton et al., 2008). These VSAs are generally integrated into numerical models with a topographical wetness index, which is generally only accurate when applied to small hill-slope catchments with a fine mesh (Todini, 2007). This integration also involves complex soil moisture and groundwater interactions between distributed landscapes within a watershed.

Evapotranspiration (ET) is a significant component of the hydrological cycle where water is removed from the watershed and enters the atmosphere. ET can account for the removal of an average of 440 mm yr^{-1} in Atlantic Canada and rates are observed to be increasing with time (Fernandes et al., 2007). This represents almost 45% of the annual average precipitation, as opposed to 70% in much of the US (Bedient and Huber, 1992). Potential ET (PET) is the amount of water removed from a uniformly vegetated area with an unlimited supply of water. In reality, water may not be available because surfaces are dry or PET may be limited by plant or soil cover. Actual ET is the amount of water removed after availability and limiting factors have been accounted for. A common and complex method used to calculate PET is the Penman-Monteith equation. This method can be expressed as described in Equation [2], where λ is the latent heat flux density (MJ m^{-2} d^{-1}), E is the depth rate of evaporation (mm d^{-1}), Δ is the slope of the saturation vapour pressure-temperature curve (kPa $^{o}C^{-1}$), H_{net} is the net radiation (MJ m^{-2} d^{-1}), G is the heat flux density to the ground (MJ m^{-2} d^{-1}), ρ_{air} is the density of the air (kg m^{-3}), c_p is the specific heat at constant pressure (MJ kg^{-1} $^{o}C^{-1}$), e_z^o is the saturation vapour pressure of air at height z (kPa), e_z is the water vapour pressure of air at height z (kPa), γ is the psychrometric constant (kPa $^{o}C^{-1}$), r_c is the plant canopy resistance (s m^{-1}) and r_a is the diffusion resistance of the air layer (s m^{-1}) (Neitsch et al., 2011).

$$\lambda E = \frac{\Delta \cdot (H_{net} - G) + \rho_{air} \cdot c_p \cdot (e_z^o - e_z)/r_a}{\Delta \cdot \gamma(1 + r_c/r_a)} \quad [\ 2\ ]$$

These terms integrate data including wind speed, humidity, temperature, solar radiation and plant parameters, such as leaf area index (LAI) and vegetation stomatal conductance. Actual ET can then be estimated by making adjustments for conditions, such as LAI, soil cover, plant water use, snow cover, soil moisture and moisture-depth availability, as done in SWAT (Neitsch et al., 2011).

If water does not contribute to runoff, re-enter the atmosphere or become stored within the subsoil it will percolate to lower soil layers. Soils above their field capacity may also contribute to lateral, shallow groundwater flow. After water percolates through the soil profile it enters a groundwater aquifer. Groundwater flow is most commonly modelled with a reservoir recession approach, such as that used in SWAT, described in Equation [3]. This equation simulates the daily groundwater outflow from a Hydrological Response Unit (HRU) to the stream channel ($Q_{gw,i}$, mm) based on the groundwater outflow from the previous day ($Q_{gw,i-1}$, mm), water entering the aquifer on the current day ($W_{rchrg,sh}$, mm) and a characteristics groundwater recession constant (α_{gw}, day^{-1}) (Neitsch et al., 2011).

$$Q_{gw,i} = Q_{qw,i-1} \cdot \exp(-\alpha_{gw} \cdot \Delta t) + w_{rchrg,sh} \cdot (1 - \exp(-\alpha_{gw} \cdot \Delta t)) \quad [\ 3\ ]$$

Other groundwater simulation methods include reservoir approaches that can include multiple linear or non-linear reservoirs. These can be used to conceptualise and simulate contributions from different aquifers, such as unconfined shallow soil aquifers, deep hard rock aquifers or artesian aquifers. Seasonal constants or highly distributed partial-differential equations based on governing groundwater principles may also be used for groundwater flow simulations.

Groundwater flow is generally identified by inspecting hydrographic data with a variety of methods. This may include simple graphical separation, application of digital filters or complex field studies using artificial or natural tracers. Most of these methods are rather subjective and somewhat arbitrary, except natural tracer tests. Identifying groundwater flow and surface flow contributions is critical in many hydrological applications, particularly Non-Point Source (NPS) contaminant modelling, because surface runoff drives the generation and transportation of many NPS contaminants.

Natural isotope tracer studies are one of the most objective means to separate components of the storm hydrograph (Klaus and McDonnell, 2013). These studies focus on identifying pre-event and event water contributions to the stream hydrograph, or old and new water. Isotopes commonly used to fingerprint these different components are Oxygen-18 (^{18}O) and Deuterium (^{2}H). Old water is generally attributed to groundwater flow and new water attributed to surface runoff. Isotope concentrations of event water (C_e, mg L^{-1}), pre-event water (C_p, mg L^{-1}) and stream flow (C_t, mg L^{-1}) are identified along with the stream flow rates (Q_t, m^3 s^{-1}). A mass balance approach is then used to estimate flow contributions from pre-event water (Q_p, m^3 s^{-1}) and event water (Q_e, m^3 s^{-1}), as described in Equations [4] and [5] (Klaus and McDonnell, 2013).

$$Q_t = Q_p + Q_e \qquad [\ 4\ ]$$

$$C_t Q_t = C_p Q_p + C_e Q_e \qquad [\ 5\ ]$$

These tracer tests have challenged the conceptualization of runoff generation because pre-event water has been observed to dominate the storm hydrograph in many natural, humid systems (Klaus and McDonnell, 2013). The capabilities of these studies can be extensive, utilizing multiple tracers to identify multiple flow components, such as soil water and surface storage. However, fundamental assumptions for this technique need to be realistic and some of these assumptions have proven to be problematic, such as positively identifying different water source components (Klaus and McDonnell, 2013). This technique is also resource intensive and largely lies within the realm of academic research, not conventional watershed management.

Vegetation conditions affect watershed hydrology and large scale vegetation alterations can have significant and detrimental impacts on the natural water cycle. Deforestation is generally recognised to increase surface runoff volume, runoff intensity, runoff frequency and increase total water yields (Stanley and Arp, 2002; Lavigne et al., 2004). This hydrological influence comes from many different elements. Interception storage of a typical forest canopy can range from 0.5 to 2 mm (Pike et al., 2010). The forest floor is also capable of storing additional water compared to deforested areas (Pike et al., 2010). Moisture is also more readily transpired from the canopy and leaf biomass than the soil profile, even though short term evaporation rates may be faster for surficial soils of deforested plots (Pike et al., 2010). Vegetation also impacts winter hydrology, particularly during the spring melt. The snowpack distribution and melt rate are also influenced by surface cover; deforested areas tend to have increased melt rates and larger snow packs (Stanley and Arp, 2002). Considering vegetation effects on hydrological processes can be very important in many situations.

When runoff concentrates into channels, methods used to describe its movement shift to hydraulically based principles. This water may still evaporate, percolate into the groundwater aquifer or move within the hyporheic zone; however, in humid regions the majority of this water remains in the channel. Channel hydraulics and river systems are complex elements of the hydrological cycle and discussed in detail in Section 2.2.

2.2 Channel Hydraulics and River Systems

Flow routing methods can range from lumped hydrologic transformation models, to complex and distributed hydraulic models. Hydrological models generally transform water volumes through river reaches using basic continuity approaches at relatively coarse time-steps. Hydraulic models employ governing hydraulic principles, such as the Saint Venant equations (Merritt et al., 2003).

Manning's equations is one of the most fundamental empirical approaches in uniform flow hydraulics, where flow velocity is a function of the longitudinal slope, hydraulic radius and channel roughness. Combined with the variable storage routing method, daily flow volumes can be computed based on Equations [6] and [7], where channel outflow at the end of the time-step ($q_{out,2}$, m^3 s^{-1}) is a function of the time-step duration (Δt, s), reach travel time (TT, s), average inflow rate ($q_{in,ave}$, m^3 s^{-1}), outflow at the start of the time step ($q_{out,1}$, m^3 s^{-1}), and volume stored in the reach at the start of the time-step ($V_{stored,1}$, m^3). This is one approach used in SWAT (Neitsch et al., 2011).

$$q_{out,2} = \left(\frac{2 \cdot \Delta t}{2 \cdot TT + \Delta t}\right) \cdot q_{in,ave} + \left(1 - \frac{2 \cdot \Delta t}{2 \cdot TT + \Delta t}\right) \cdot q_{out,1} \qquad [\ 6\ ]$$

$$TT = \frac{V_{stored,1}}{q_{out,1}} \qquad [\ 7\ ]$$

In conjunction with the variable storage routing method, peak flow rates can be approximated with a modified rational formula and a peak rate adjustment factor to affect erosion and sediment transport processes (Neitsch et al., 2011).

When concerned about detailed hydrographic information, more physically-based approaches need to be considered. This may be required for hydraulic structure design, detailed sediment transport assessments, and flood wave simulations, where varied and unsteady flow conditions may be present. This typically requires numerical solutions to the Saint Venant equations or its various approximations. In their full form, the Saint Venant equations form the basis of complete dynamic models, which consist of a continuity equation and conservation of momentum equation (French, 2001). A simplified form of the Saint Venant equation commonly applied to river systems in hydrological modelling is the kinematic wave model, governed by the equation:

$$\frac{dQ}{dt} + \epsilon V \frac{dQ}{dx} = 0 \qquad [\ 8\ ]$$

In Equation [8], Q is flow ($m^3\ s^{-1}$), ϵ is a coefficient dependant on the friction resistance equation used and V is velocity ($m\ s^{-1}$). This equation makes the assumption that local acceleration, pressure forces and convective acceleration are negligible and that gravity forces and friction forces are equal. Most hydraulic approaches typically assume velocity is uniformly distributed across the channel's vertical profile for simplification (Henderson, 1966). One-dimensional and two-dimensional models are typically depth-averaged (Bureau of Reclamation, 2006). In reality this velocity profile follows a parabolic shape and can be influenced by many factors, such as turbulence conditions, bed form and channel features. Lateral velocity profiles also follow characteristic shapes and vary depending on channel features. Velocity and shear stress influence one another and velocity or shear stress approaches are common methods used in sediment transport and channel erosion simulations, particularly when considering incipient motion criteria (Bureau of Reclamation, 2006).

In hydrological applications, river reaches are often simulated as 1-D elements and typically distributed based on stream order. When focusing on detailed river processes, refined spatial and temporal resolution are often required but 1-D models are still the most popular for long river reaches (Bureau of Reclamation, 2006). However, 1-D models can be limited when lateral and vertical flow is significant, such as in complex flooding scenarios and around channel features like the inside and outside of a meander. Two-Dimensional models overcome many of these limitations when detailed reach simulations are required. Three-Dimensional models are the most realistic; however they are complex, resource intensive and most susceptible to numerical instability (Bureau of Reclamation, 2006). All of these models typically follow a finite-difference method but finite-element or finite-volume frameworks may also be used (Bureau of Reclamation, 2006).

River systems are intimately linked and influenced by their upland drainage areas. Stable channel forms, typical in hydraulic engineering contexts, lack some of the dynamic considerations present in river systems. Naturally stable channels are in a state of dynamic equilibrium, which is a product of the complex interplay of regional geology, climate, topographic gradient, the river's history and drainage basin hydrology. This equilibrium is also primarily controlled by flow regimes and sediment loads (Rosgen, 1996; Lord et al., 2009). Altering these two factors is the primary stressor to fluvial processes and geomorphology affecting channel stability. When flow regimes are altered, sediment deposition or scour can be expected. When sediment loads are altered, channel aggradation and degradation can change flow characteristics. These impacts can propagate significant distances upstream and/or downstream beyond an initial disturbance location (Lord et al., 2009). Classifying river systems based on physical characteristics can help land mangers understand the complex behaviour of these systems and determine if they are in a state of instability or dynamic equilibrium. If channels are not stable, this identification can help determine what stage of the evolutionary morphological sequence a reach is currently in. All these considerations are important to prescribe and conduct effective mitigation and restoration efforts. An example channel classification system included in Figure 3 (Church, 1992) and other classification systems are available (Rosgen, 1996).

Rivers are often described as dynamic and open ecosystems that form highly productive "spirals" for nutrient cycling (National Research Council, 1992). Incised and rapidly eroding channels may be initiated by anthropogenic disturbances to a reach's natural dynamic equilibrium. This can impair these productive qualities by lengthening the nutrient "spiral" from increased sediment transport rates, isolate the reach from its riparian environment and many other detrimental impacts. Degraded water quality and aquatic habitat are common in disturbed reaches, such as increased turbidity and Total Suspended Solids (TSS) and smothering of gravel spawning habitat for salmonid species (Canadian Council of Ministers of the Environment, 2002).

The dynamic and complex nature of river systems requires integrated, multi-disciplinary systems approaches. Reach specific approaches are often insufficient (Lord et al., 2009). The discipline of river engineering alone requires skills in sediment transport analysis, hydrology, hydraulics and fluvial geomorphology (Remus and Jonas, 2010). However, river engineering, within an aquatic restoration context, is often the last course of action because it is expensive, complex and risky. Effective land management practices, enabling natural restoration, are primarily recommended (National Research Council, 1992).

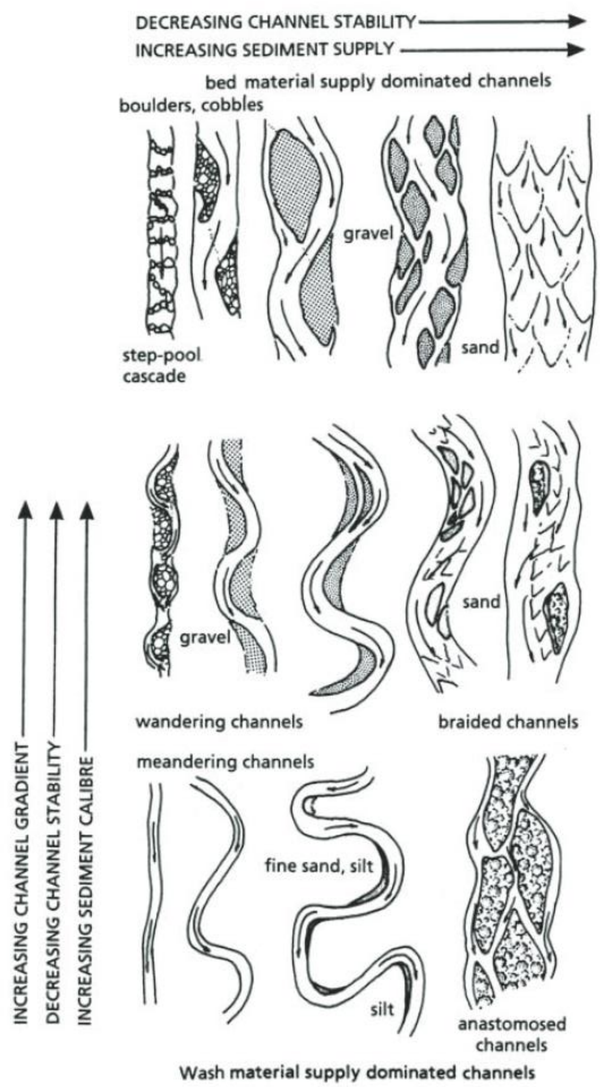


Figure 3. Channel classification system (Church, 1992).

2.3 Erosion and Sedimentation Processes

Erosion is a significant cause of land degradation and eroded sediments are a leading cause of waterway impairment around the world (Vanoni, 2006; Tamene and Vlek, 2008; United States Environmental Protection Agency, 2013). While many erosion and sedimentation processes are completely natural, anthropogenic changes in the environment can accelerate these processes to dangerous levels. Sediments are currently listed as the fifth leading cause of waterway impairment in the US (USEPA, 2013) and are estimated to cause damages of $16 billion annually in North America (Osterkamp et al., 1998). Within Eastern Canada and the northeast US, stream erosion and suspended sediments are among the leading concerns of stormwater runoff (GEMTEC, 2008). Sediments are also one of the most difficult water quality constituents to accurately predict in current watershed and stream models (USEPA, 2006). The study of erosion, sediment transport and deposition is a complex topic subject to much uncertainty (Bureau of Reclamation, 2006). While the physical principles behind surface and channel sedimentation processes are similar, the technical approaches between these two categories, and within these two categories, vary widely.

The Universal Soil Loss Equation (USLE) was among the first numerical tools created to predict surface erosion from water runoff processes. It was developed by the United States Department of Agriculture (USDA) as a soil conservation tool to assist agricultural land managers in reducing soil erosion rates from agricultural operations (Wischmeier and Smith, 1965). It is an empirical tool developed from decades of soil erosion experiments and plot studies. Since the inception of the USLE it has been modified into several different forms and utilized, in-part or as a whole, to predict erosion rates around the world (Merritt et al., 2003). The Revised USLE (RUSLE), and the RUSLE adapted for Canada, is an updated version that includes various sub-factors and adjustments for seasonal conditions (Wall et al., 2002). Another USLE derivative utilized in SWAT, the Modified USLE (MUSLE), is expressed below:

$$sed = 11.8 \cdot \left(Q_{surf} \cdot q_{peak} \cdot area_{hru}\right)^{0.56} \cdot K \cdot C \cdot P \cdot LS \cdot CFRG \qquad [\ 9\ ]$$

Equation [9], where *sed* is the sediment yield on a given day (metric tonnes day^{-1}), Q_{surf} is the surface runoff volume (mm ha^{-1}), q_{peak} is the peak runoff rate (m^3 s^{-1}), $area_{hru}$ is the area of the Hydrological Response Unit (HRU, ha), K is a soil erodibility factor (0.013 tonnes m^2 hr m^{-3} $tonnes^{-1}$ cm^{-1}), C is a cover factor (dimensionless), P is a support practice factor (dimensionless), LS is a topographic factor (dimensionless) and CFRG is a soil coarse fragment factor (dimensionless) (Neitsch et al., 2011).

In reality, physical erosion processes are much more complex than described in the USLE. Process-based operating equations may be used to independently simulate the four main types of erosion process: sheet, rill, gully and channel erosion. This may also include the three separate stages for each process: detachment, transport and deposition (Merritt et al., 2003). Many methods vary from model to model. They also become increasingly complex, requiring extensive input data, as physically-based simulations attempt to better represent reality. Even these complex model can be limited by basic issues, such as complex terrain leading to complex overland flow patterns. Flow concentration patterns affect the energy content of water leading to complex erosion and deposition patterns, and overland flow patterns can be difficult to predict even with distributed models (Steichen et al., 2008). The continuity equation governs many of these physical approaches, and is given as:

$$\frac{d(AC)}{dt} + \frac{d(QC)}{dx} = e_i + e_r \qquad [\ 10\ ]$$

In Equation [10], A is the cross sectional area of a planar slope (m^2), C is the sediment concentration in the flow (kg m^{-3}), Q is the flow (m^3 s^{-1}), e_i is the net rate of inter-rill erosion (kg m^{-2} s^{-1}), and e_r is the net rate of erosion by rills (kg m^{-2} s^{-1}) (Morgan, 2011). This equation can be expanded to account for different sediment size classes, which will have different erosion, transport and deposition patterns. An example of a process-based erosion equation, as used in Water Erosion Prediction Project (WEPP) model, can be expressed by:

$$e_i = K_i \cdot I^2(1 - F^{0.34PH})e^{-2.5G}\, R_s/W \qquad [\ 11\ ]$$

$$e_r = K_r(\tau - \tau_c)\left[1 - C/k_t\tau^{3/2}\right] \quad [\ 12\ ]$$

In Equation [11], K_i is the inter-rill erodibility (s m^{-1}), I is the intensity of the rainfall (m s^{-1}), F is a fraction of soil protected by the plant canopy, PH is the height of the plant canopy (m), G is the fraction of soil cover by ground residue, R_s is the spacing of the rills (m) and W is the width of the rills computed as a function of the flow discharge (m). In Equation [12], K_r is the erodibility of the soil (s m^{-1}), τ is the shear stress acting on the soil (Pa), τ_c is the critical flow shear stress for soil detachment (Pa), C is the sediment load in the flow (kg m^{-3}) and k_t is a sediment transport coefficient (Nearing et al., 1989; Morgan, 2011). These equations, and similar approaches, incorporate a sediment transport capacity concept, which accounts for sediment fluxes and deposition patterns. Data requirements and parameterization is extensive when utilizing such approaches, while resultant uncertainty is generally substantial.

In-stream erosion, sediment transport and deposition methods can be physically similar to those of overland flow but generally utilize altered approaches. There are many unique and complex approaches used to describe the movement of sediments within river systems. Sediment transport functions can be defined as regime, regression, probabilistic or deterministic approaches (Bureau of Reclamation, 2006). In SWAT, sediment transport in the channel is a function of deposition and degradation. Deposition occurs when the maximum sediment concentration is exceeded and is described, in part, by the simplified Bangold equation given below:

$$conc_{sed,ch,mx} = c_{sp} \cdot {v_{ch,pk}}^{spexp} \quad [\ 13\ ]$$

In Equation [13], $conc_{sed,ch,mx}$ is the maximum concentration of the sediment that can be transported by the water (kg L^{-1}), c_{sp} is a user defined coefficient, $v_{ch,pk}$ is the peak channel velocity (m s^{-1}) which is approximated with a peak rate adjustment factor, and *spexp* which is a user defined exponent (Neitsch et al., 2011).

Channel erosion methods typically take a form similar to that used in SWAT, given as:

$$\varepsilon = k_d \cdot (\tau_e - \tau_c) \cdot 10^{-6} \qquad [\ 14\ ]$$

In Equation [14], ε is the erosion rate (m s^{-1}), k_d is an erodibility coefficient (cm^3 N^{-1} s^{-1}), τ_e is the effective shear stress (N m^{-2}) and τ_c is the critical shear stress (N m^{-2}) (Neitsch et al., 2011). This equation may be used to describe bed and/or bank erosion rates. Critical shear stress can be approximated with field jet tests, empirical relations, flume studies, Shields' diagram and more (Clark and Wynn, 2007). The effective shear stress can also be defined by a number of methods. SWAT utilizes the expression below:

$$\frac{\tau_e}{\gamma_w \cdot d \cdot S_o} = \left(1 - \frac{SF_{bank}}{100}\right)\left(\frac{W}{2 \cdot P} + 0.5\right) \qquad [\ 15\ ]$$

In Equation [15], γ_w is the specific weight of water (N m^{-3}), d is the depth of water (m), S_o is the channel slope, SF_{bank} is the portion of shear stress acting on the bank, W is the top width of the channel (m) and P is the wetted perimeter of the bed (m). Other approaches can be used to predict channel erosion, suspended sediment load and bed load transportation rates. Within SWAT alone there are four stream power models that can be used to predict bed load transport capacity (Neitsch et al., 2011).

In a stream or river, material is generally classified to be a part of the dissolved load, suspended load or bed load. Classification of these different transport loads depend on particle grain size and channel flow energy (Lord et al., 2009). Suspended loads are generally controlled by the production and delivery rates of upland drainage areas, while the bed load is more related to a channel's flow energy (Lord et al., 2009). Suspended loads tend to be the focus of watershed scale sediment studies, with little mention of dissolved load or bed load. However, the bed load, which is typically composed of coarse sediments, significantly affects channel morphology. Channel morphology is primarily driven by flow rates achieving bankfull discharge, which usually occurs every year or two (Lord et al., 2009). Annual erosion yields also tend to be dominated by large, infrequent flow events (Wigmosta et al., 2007). Unstable channels have elevated sediment yields and it may take centuries for stream channels to evolve though different morphological stages into a stable channel. During this time the majority of sediment yields may be attributable to channel erosion (Ontario Ministry of the Environment, 2003; Staley et al., 2006; Clark and Wynn, 2007). Even stable channels can contribute significant portions of watershed sediment yields. Accounting for sediment sources, be that upland surface erosion or channel erosion, remains to be a significant challenge in many modelling applications. This may also be a source of significant conceptual error in many watershed models and sediment related studies that fail to recognize different erosion and sedimentation processes.

Watershed modelling studies considering channel erosion processes are not always well documented and even those that are, demonstrate substantial uncertainty. One watershed study simulated channel erosion with the CONCEPTS, GWLF and SWAT model, and resulted in annual sediment yield from stream erosion of 4, 8 and 1500 tonnes yr^{-1}, respectively. This compared to an annual erosion rate of 41 tonnes yr^{-1} estimated from bank erosion pins (Staley et al., 2006). This demonstrated the significant amount of uncertainty that channel erosion models can exhibit. Even when channel erosion processes are simulated it is difficult to differentiate between various sources during model calibration.

One developing technology concerning erosion and sedimentation processes is that of sediment fingerprinting. This technology recognizes that the design and implementation of effective management strategies for sediment control require accurate information about the relative sediment contributions from different sources (Mukundan et al., 2012). Composite fingerprinting approaches seek to identify source types, such as field, channel and road sediments, by identifying multiple physical and chemical properties among source types. Some of these properties include radionuclides, elemental metals, spectral reflectance, isotopes and magnetism. Statistical tests are used to discriminate source types with significantly unique properties. Suspended sediments collected at the catchment outlet are then proportioned into different source types by a mixing model that is fitted iteratively by minimizing an objective function (Minella et al., 2008). Some limitations and challenges of this approach are that sediment tracer properties are assumed to be conservative in fluvial systems. In reality this may not be true, which can be attributable to many complex processes, such as the enrichment in fine and/or organic matter from selective erosion or deposition (Mukundan et al., 2012). Sediment fingerprinting in large basins (>500 km^2) may also be difficult due to heterogeneity in source material (Collins et al., 1998).

Erosion and sedimentation processes span many fields of study and an exhaustive review is outside the scope of this research. Key erosion and sedimentation principles have been discussed, including those utilized in SWAT. Other key principles that are considered to be worth additional consideration were also mentioned. Ice scour, cohesive sediments and road erosion are among a few topics not addressed in this research; however, they may be significant within the context of erosion and sedimentation processed for select watersheds in military lands (Milburn and Prowse, 1996; Bureau of Reclamation, 2006; Elliot et al., 2009; Donigian et al., 2010).

2.4 Model Review

A review of select models was conducted for those applied to military lands or with unique features that may be valuable for military land management applications. Additional literature reviews concerning model capabilities and applications are provided by Deinlein and Böhm (2000), Merritt et al. (2003) and Beckers et al. (2009), to name a few. The SWAT model was ultimately selected for this study for reasons described in Section 4.1. A detailed description of the SWAT model is included in Section 2.8.

2.4.1 USPED

The Unit Stream Power Erosion Deposition (USPED) model, or 3-D RUSLE, utilizes the USLE but converts the LS factor into a continuous topographic factor based on upslope contributing area and slope steepness (Warren et al., 2005). The model is executed in a GIS interface and better accounts for flow convergence across complex terrain by utilizing a grid cell mesh. Sediment deposition is also considered, unlike in many of the USLE derivatives. The sediment transport capacity is derived in 2-D space based off a transportability coefficient, water depth, upslope area, slope and profile curvature (Warren, 1998; Warren et al., 2005). An issue with this approach is that erosion parameters used in this method were developed for simple plane fields under detachment limited conditions (Mitasova and Mitas, 2001). This type of model is more of a geospatial model and not a hydrological model.

2.4.2 LISEM

The Limburg Soil Erosion Model (LISEM) is a physically-based agricultural erosion model that is used to simulate single rainfall events in small catchments (De Roo et al., 1996). Splash and flow erosion are simulated along with sediment transport and deposition processes from stream power principles. A four-point finite difference solution of the kinematic wave equation is used to route overland flow through a distributed cell network (De Roo et al., 1996). It is unique among other models because it specifically simulates wheel tracks and roads smaller than pixel size, as displayed in Figure 4 (De Roo et al., 1996). Both tracks and ruts act as features that reduce local infiltration and concentrate overland flow (Steichen, 2008). Sub-cell elements generate different runoff rates depending on infiltration characteristics; then the average water volume is calculated over the entire cell for routing. Erosion processes are also lumped over the entire cell. This model has seen little application in North America; it was developed and is mostly utilized in Europe.

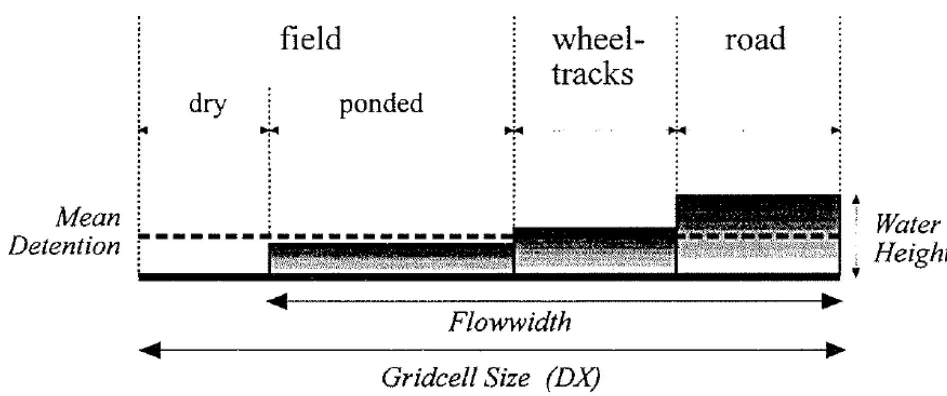


Figure 4. LISEM sub-cell distribution for runoff generation.

2.4.3 WEPP

The Water Erosion Prediction Project (WEPP), developed by the USDA, is a processed-based erosion model that was developed to create enhanced predictive capabilities over classical empirical models, such as the USLE. WEPP has a cross-section hillslope module, a small watershed module and a linear road module, all used for the primary purpose to evaluate sediment yields over extended periods of time. Climate data is driven by a stochastic weather generator. Overland flow elements are assigned to lumped hillslope elements of variable profiles. Alternatively, hillslope elements can be divided into cascading planes or a distributed cell mesh. Overland flow routing is calculated with a kinematic wave approximation or a regression equation derived for a range of slope steepness, lengths, surface roughness coefficients, soil textural classes and rainfall distributions. Steady state conditions at the peak runoff rate are assumed for erosion calculations. Inter-rill, rill and ephemeral channel erosion is modelled considering detachment-limited and transport-limited conditions on a daily time-step. WEPP is heavily focused on the inter-storm variations in determinant system properties such as soil erodibility, soil moisture, soil surface conditions, plant canopy and ground cover (Nearing and Hairsine, 2011). This model is recommended for relatively small watersheds and has limited capabilities in modelling perennial streams (Ascough et al., 1997).

In WEPP: Road, sediment yields are calculated assuming several standard configurations of road segments, including the cut-slope, fill-slope, ditches, ruts and traffic surfaces. Input parameters for this road module include soil texture, road geometry, buffer geometry, traffic intensity and road surface conditions (Elliot et al., 2009). Mitigation efforts can be modelled by shortening slope length, constructing water bars, reducing traffic loads or hardening road surfaces. This tool is readily available online, where users can quickly evaluate sediment yields for select road configurations.

2.4.4 HSPF

The Hydrological Simulations Program - Fortran (HSPF) is a comprehensive hydrological and water quality model (Bicknell et al., 1996). It operates on a time-step of one minute to one day and can be used for continuous, multi-year simulations. It is generally lumped or semi-distributed based on the definition of relatively homogeneous Hydrological Response Units (HRUs). As with many lumped or semi-distributed models, flow is generally routed from the response unit directly to the channel. Inter-HRU interactions are generally not simulated but may be for some applications. A basic example of an HRU definition approach is displayed in Figure 5 (Koua et al., 2013). Soil detachment, transport and deposition can all be simulated. The 1-D river model also includes physical processes, such as sediment transport, deposition and scouring. Explicit representation of vegetation is limited (Beckers et al., 2009). HSPF has been combined with other models to create hybrid modelling frameworks for complex hydrological, hydraulic and sedimentation processes (Donigian et al., 2010). Due to its complexity, this model requires a significant amount of time and resources for development, data management and calibration (Merritt et al., 2003). The model's structure is also considered to be not as user-friendly compared to other models (Beckers et al., 2009).

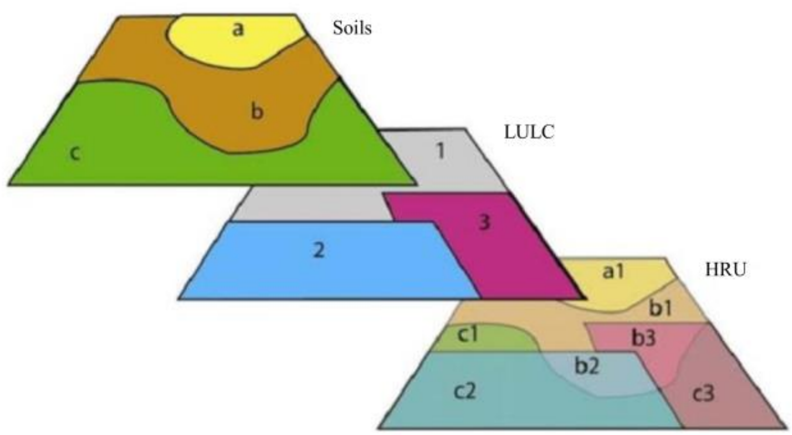


Figure 5. Example HRU definition.

2.4.5 DHSVM

The Distributed Hydrology Soil Vegetation Model (DHSVM) was developed to represent the effects of topography and vegetation on water fluxes through the landscape (Wigmosta et al., 1994). This distributed model is typically applied at a 10-100 m resolution on an hourly time-step for multi-year simulations. Two vegetation layers are included in this model, which are integrated into physically based ET methods and snow related processes (Beckers et al., 2009). Groundwater movement is simulated with a quasi-3-D routing scheme. Return flow and saturated overland flow occur when the water table intersects the ground surface. Road hydrology can be described with detailed information on network geometry and interconnectivity. The spatial and conceptual framework in this model is outlined in Figure 6 (Wigmosta et al., 1994). This distributed cell mesh is common among most distributed models. While DHSVM is a hydrological model, it has been modified to include sediment models including hillslope erosion, road erosion and sediment channel-routing (Doten et al., 2006). This has also included integration of the Hillslope Erosion Model (HEM), which utilizes the kinematic-wave and sediment continuity equation to route sediments across a planar hillslope or series of cascading hillslope segments (Wigmosta et al., 2007). The model is highly complex, requires substantial input data and only limited efforts have been made to incorporate it with a user-friendly interface. It is also primarily utilized in the Pacific Northwest, and on highly instrumented watersheds (Beckers et al., 2009).

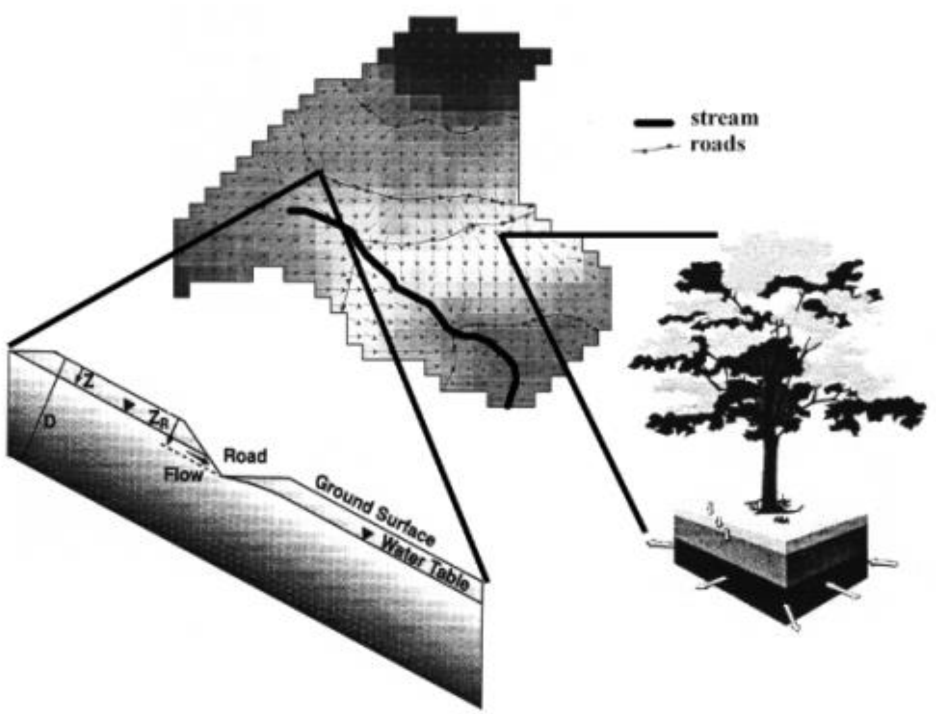


Figure 6. Spatial and conceptual framework of DHSVM.

2.4.6 EROSION 3-D

EROSION 3-D is a physically-based model that simulates soil detachment, sediment transport and surface runoff separately. It is designed to predict event-based runoff and erosion yields by considering common parameters, such as soil erodibility, vegetation cover and topographical conditions. Initial soil moisture conditions are required for input data, which can significantly affect runoff simulations (Deinlein and Böhm, 2000). Temporal and spatial resolutions used in this model are relatively high, with a 1-15 minutes time-step and 5-20 m cell grid format being most common. Input data requirements are moderate and the model is integrated with a GIS interface (Deinlein and Böhm, 2000). Runoff is calculated with a modified Green and Ampt infiltration method, which is routed though cells until a concentration threshold is reached (Schmidt, 1991). Surface relief changes, winter erosion and runoff inhibition structures can be simulated. This model has seen little application in North America; it was developed and is mostly utilized in Europe.

2.5 Watershed Management and Modelling in Military Lands

There are various tools, approaches and models that have been reported in the literature related to research and management within military lands. This section will highlight these methods to provide a context of potential directions for watershed research and management strategies within Canada. The US has contributed considerable resources within this field and therefore dominates most of the related literature. These approaches include methods, such as water quality regression analysis, geospatial erosion modelling, distributed hydrological modelling and traffic disturbance modelling.

Water quality regression models have been developed for TSS, total nitrogen, organic carbon and organic nitrogen at Fort Stewart, Georgia (Jager et al., 2011). This research monitored headwater drainage affected by military training with baseflow grab samples and rising-stage samples for rain events on 6 days between August 2008 and June 2009. Watershed attributes, selected a priori, were used to predict water quality variables including percent wetland, forest and bare ground/road density. Elapsed time since last managed burn, use of off-road vehicles, use of heavy training equipment, antecedent rainfall, rainfall events and growing seasons were also considered. TSS was positively associated with off-road vehicle use, bare ground and road density. Correlation between log-transformed water quality variables ranged from 0.56-0.69 (Jager et al., 2011).

Surface erosion assessments have also been developed for military lands using derivatives of the USLE with a distributed geospatial analysis (Warren et al., 1989; Warren, 2005; Wigmosta et al., 2007; Dalton, 2008). A distributed GIS application of the USLE, with a 50 m cell resolution, has been developed for Fort Hood, Texas (Warren et al., 1989). Cover factors were estimated with LANDSAT multispectral scanner imagery, unsupervised land cover classification and vegetation cover transects. Cover factors ranged from 0.02 to 0.17; however, these were suspected to be conservative because they do not account for physical disturbances caused by training manoeuvres. Geospatial erodibility indexes can be classified from this type of approach, where low erosion potential can correspond to a low index number, as displayed in Figure 7 (Warren et al., 1989).

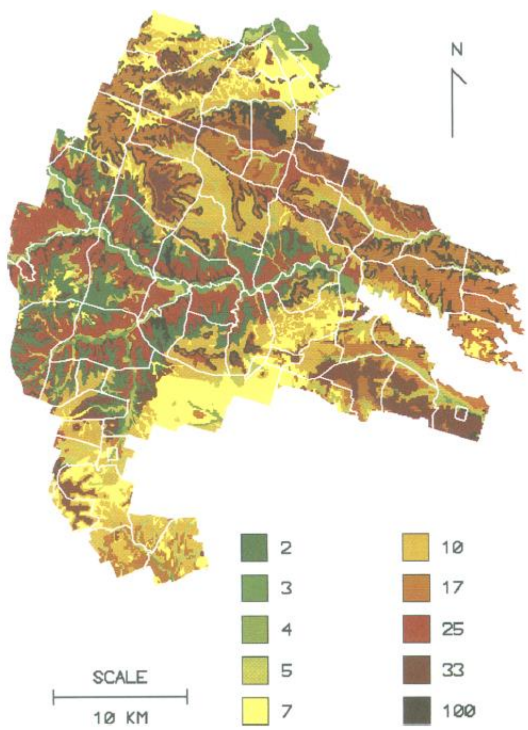


Figure 7. Erodibility index map from Fort Hood, Texas.

The RUSLE has been utilized in Fort Riley, Kansas (Steichen et al., 2008). A Total Training Days intensity factor was integrated into this model based on training area usage provided by the Range Control office. Soil moisture mapping was also included in this study because it is an important element of the hydrological cycle and affects off-road vehicle traffic. Moisture mapping utilized Land Surface Temperature and Normalized Difference Vegetation Index GIS imagery, in conjunction with field measurements. Gully erosion, field buffers, stream crossing evaluation and stream sediment characterization were also research tasks in this approach. A GIS driven nLS model (surface roughness, slope and slope length) was used to predict gully head formation, an important erosion feature. Hardened stream crossings were also identified as conduits for increased contaminant transport to stream waters (Steichen et al., 2008).

The RUSLE has also been used in Camp Atterbury, Indiana across selected erosion plots to prioritize rehabilitation efforts (Dalton, 2008). Unique in this approach is that vegetation cover factors were estimated based on a regression analysis, including vehicle manoeuvre impact miles per hectare. This analysis was developed from site specific field observations. The approach was also integrated with economic and environmental considerations, as part of a decision framework strategy.

The USPED has been applied to Fort Hood, Texas and validated using the radioactive isotope ^{137}Cs within the soil profile (Warren, 2005). The distribution of ^{137}Cs in the soil profile on reference sites was compared to disturbed sites to estimate erosion and deposition patterns across a manoeuvre prairie watershed. Modelled estimates, compared to field observations produced a RMSE of 7.96 ± 0.62%. A lumped vegetation cover factor was determined from a regression analysis with LANDSAT 5 Thematic Mapper images and vegetation cover transects for use in the USPED model. The lumped cover factor approach, variable soil properties, soil redistribution from military activity (not erosion and deposition) and variable ^{137}Cs fallout distribution may have accounted for errors within this approach. Two other forms of the USLE were also used in this study and all erosion models were subsequently applied to

Camp Guernsey, Wyoming and Fort McCoy, Wisconsin (Warren, 2005). These approaches do not quantify hydrological conditions, net sediment delivery to stream channels, channel processes or water quality conditions. The USPED model has also been applied to Fort Benning, Georgia, which further considered SCS CNs in a weighted estimate as part of a flow accumulation factor (Liu et al., 2007).

Complex, more process-based models have also been applied to military training ground and integrated into management frameworks. This has included application of SWAT at Camp Atterbury, Indiana within a training load optimization framework (Dalton, 2008). EROSION 3-D has been used in Germany to predict event-based design storm erosion, deposition and sediment yields along with long-term erosion estimates within a military training area (Deinlein and Böhm, 2000).

WEPP is another physically-based modelling tool that has been used to assess erosion and deposition at Camp Atterbury (Gaffer et al., 2008). The geospatial interface watershed module, GeoWEPP, was used and general erosion rates were highly correlated with qualitative field observations. Roads and trails were included in this analysis but recommended for additional evaluation (Gaffer et al., 2008). WEPP: Road, a version designed to evaluate erosion across road segment, has also been integrated into multi-spatial scale hybrid modelling projects for military installations to quantify road erosion contributions at the watershed scale (Donigian et al., 2010).

An HSPF model has been developed for Fort Benning within a watershed modelling framework to assess impact of military management alternatives (Donigian et al., 2010). This work focused on utilizing complex hybrid modelling to integrate more robust simulations at multiple spatial scales. Enhancements were also conducted to improve channel flow and sediment transport simulations with the Environmental Fluid Dynamics Code and SEDZLJ, along with the ecosystem effects model AQUATOX. More detailed representation of the forest canopy was recognized as an important aspect for further enhancement of these modelling efforts (Donigian et al., 2010).

Hybrid modelling has also been conducted with DHSVM and HEM at the Yakima Training Center, Washington State (Wigmosta et al., 2007). This has also been integrated into a decision support framework and an adaptive management framework. This model was successfully validated with sediment yields measured from sedimentation ponds (Wigmosta et al., 2007).

Military vehicle traffic, and the effect it has on the landscape, has also received considerable attention because these effects can directly influence watershed hydrology, erosion and water quality conditions. Vegetation loss and rut depth from vehicle manoeuvres have been estimated with the Vehicle Dynamic Monitoring and Tracking System, which considers detailed vehicle properties, movement tracking dynamics and soil properties (Koch et al., 2012). A field trafficability model has also been developed for Gagetown, utilizing the Forest Hydrology Model, soil information and basic vehicle properties (Vega-Nieva et al., 2008). Soil moisture has a significant impact on soil trafficability and surficial disturbances that are caused from vehicle traffic. VSA hydrology is an important approach to consider when concerned about soil moisture conditions. These conditions affecting traffic impacts will also affect surface runoff, erosion, sediment transport and deposition patterns. Integrating these traffic impact technologies with holistic watershed models has received little attention.

2.6 Watershed Management and Modelling Strategies

Any modelling approach requires that it be integrated into a decision framework or management strategy to optimize its use and application. This is apparent with the Gagetown trafficability model, which is not integrated into an enforced management strategy, and receives little use and consideration in standard operations. A strategic approach is also necessary to develop reliable modelling tools so that land managers are confident in guiding decisions off information these models provide.

An accurate understanding of significant processes is critical. For example, stream channels have been observed to contribute the majority of sediment yields in some watersheds (Clark and Wynn, 2007). If an erosion model only focuses on surficial processes the whole system may be severely misrepresented. To overcome this potential issue the US utilizes an approach, outlined in Figure 8, for sediment Total Daily Maximum Load (TDML) assessments (Mukundan et al., 2012). If the aim is to restore aquatic habitat, focusing on erosion structures to improve water quality may not have a significant effect. Restoration of flow regimes may be more significant and is often neglected in many restoration efforts (National Research Council, 1992). Fluvial restoration approaches aim to first restore natural sediment and water regimes, followed by channel geometry and finally riparian plant communities. Land management practices are also the first course of action in restoration efforts and should only be supplemented by hard structural improvements if management practices do not enable natural restoration to occur (National Research Council, 1992).

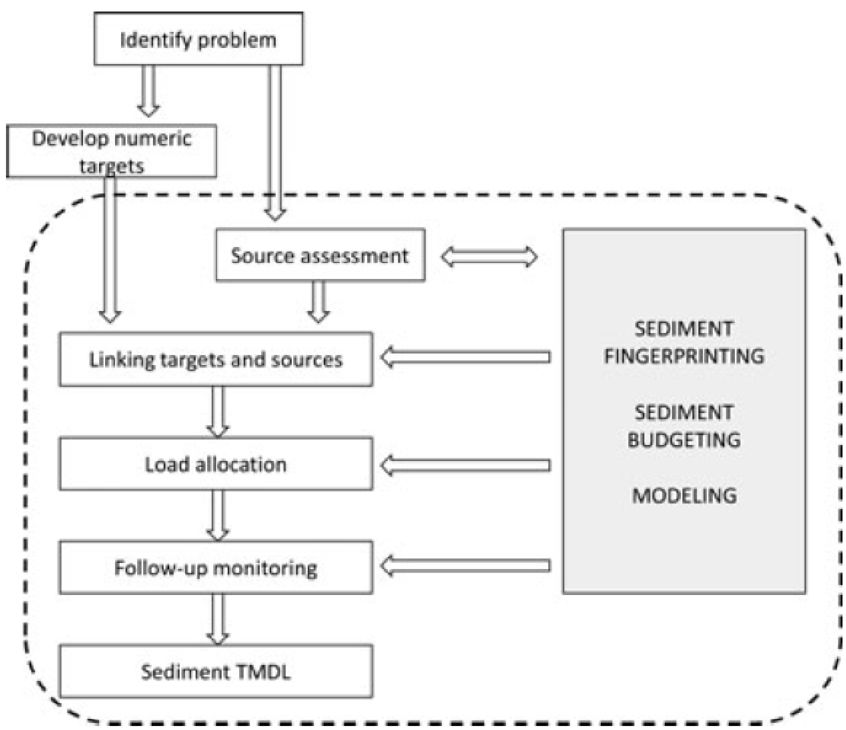


Figure 8. Sediment TDML framework.

Military training areas are recognized to require multiple spatial scales for watershed modelling assessments, and distributed approaches have also been recommended for many applications (Donigian et al. 2010). However, hybrid, multi-scale, complex, and process-based models may not be practical to consider in management scenarios. Simple models with few data requirements are often more effective for some management strategies (Grayson et al., 1992). Dealing with model uncertainty in decision making frameworks is also problematic (Todini, 2007). Differentiating between parameter uncertainty and predictive uncertainty is sometimes neglected. Assessing uncertainty is also a complex process; there are many different uncertainty approaches, and decision makers may lack effective methods to fully consider these uncertainties.

There are common misapplications and misconceptions about erosion models (Govers, 2011). This may include inappropriate time scales, such as daily reporting of USLE results. The USLE is a model designed for annual estimates, where 20 year measurement periods were often necessary to establish mean erosion rates. Models are sometimes assumed to describe processes which they do not consider. Gully erosion, tillage erosion and wind erosion can all affect soil redistribution and these processes are not always considered in some models. These processes need to be considered when interpreting validation results. Appropriate spatial scales are also important to consider and that proper consideration is given when scaling model parameters. There are also several misconceptions about erosion models. Better models, or more complex, distributed and physically-based models, are not necessarily more accurate. Accurately predicting catchment sediment yields does not always mean that the model is well calibrated and validated. Also, process based models are not always applicable in assessing alterations, even with *a priori* calibration (Govers, 2011). Model capabilities, assumptions and limitations need to be well understood if they are effectively integrated into management strategies.

Clear objectives and targets also need to be selected for watershed management strategies. This can include water quality guidelines, discussed in Section 2.7, or a Low Impact Development (LID) target to maintain the pre-development hydrological cycle (Toronto and Region Conservation Authority, 2010). Without clear objectives there are few means to assess the effectiveness of management and mitigation efforts, and little guidance to select appropriate modelling frameworks. Collaborative efforts, involving all stakeholders, need to be conducted to effectively design a management strategy. Multi-disciplinary approaches are also required and watershed modelling is not a standalone discipline capable of achieving success in this field alone.

2.7 Water Quality Guidelines and Indicators

There are few regulatory standards readily enforceable to NPS contamination in observed waterways at 5 CDSB Gagetown, with the focus on sediment related variables. There are, however, a variety of guidelines and recommended water quality standards, with the Canadian Council of Ministers of the Environment (CCME) – Canadian Environmental Quality Guidelines (CEQG) being the most widely accepted across Canada. In addition to these threshold guideline targets, there are a variety of methods that can be used to develop general water quality indicators, such as the Water Quality Index (WQI) and Severity of Ill Effects (SEV) method.

CCME CEQG for the protection of aquatic life includes sediment, turbidity and pH parameters. Turbidity targets are set at an 8 NTU increase for a 24 hour period and 2 NTU increase for longer periods from clear flow background conditions. The maximum TSS increase from clear flow background conditions is 25 mg L^{-1} for a 24 hour period and 5 mg L^{-1} for longer periods (CCME, 2002). pH ranges are also recommended to stay within 6.5 and 9 (CCME, 1996). These guidelines generally require background conditions for relative comparison, which can be difficult to establish, particularly for high flow conditions (CCME, 2002).

CCME guidelines may not be suitable for agricultural watersheds and so the National Agri-Environmental Standards Initiative (NAESI) has developed additional turbidity and TSS guidelines for these situations. These non-regulatory standards include Ideal Performance Standards (IPS) for Atlantic Canada for TSS and turbidity of 6.1 mg L^{-1} and 2.8 NTU, respectively. The recommended duration and frequency of these thresholds have not been determined, but seasonal or annual averaging periods are generally appropriate (Culp et al., 2009).

Other water quality recommendations for aquatic life include a 24 $^{\circ}$C temperature threshold for brook trout (Raleigh, 1982). Sediment loads exceeding 400 mg L^{-1} have been classified as unacceptable risk, high risk range from 200-400 mg L^{-1}, moderate risk from 100-200 mg L^{-1}, low risk from 25-100 mg L^{-1} and very low risk are those below 25 mg L^{-1} (Birtwell, 1999).

To achieve the best sense of water quality conditions and effectively communicate these conditions, several methods have been developed to integrate important factors, such as exceedance frequency, exceedance magnitude and cumulative variable effects. The SEV method considers event duration and magnitude of TSS or turbidity to predict biological effects on fish (Newcombe, 1997). However, it has been observed in some agricultural regions of New Brunswick that the SEV was poorly correlated to fish densities and conditions. Temperature alone tended to be a better predictor (Smedley, 2009). The WQI method considers multiple water quality parameters, along with their exceedance frequency and exceedance magnitude. It is more indicative of general water quality conditions, as opposed to event-based conditions (CCME, 2001). WQI results have been positively correlated to benthic communities, a correlation which may be improved by trimming the mirrored 5^{th} percentile of poor water quality parameters, effectively filtering out low frequency events that have limited influence on aquatic environments (Kilgour et al., 2013).

Within Gagetown, the WQI is likely to be an effective tool to assess general water quality conditions. Landscape conditions are most comparable to those of agricultural watersheds and so NAESI-IPS guidelines are suspected to be the most informative, where applicable. A water temperature threshold of

24^{o}C, and an acceptable pH range of 6.5-9, will also be informative indicators. Other indicators such as Fe and Mn concentrations may also be important to consider. Fe has been documented as a strong predictor of benthic communities; however, this is likely due to geological conditions (Estrada et al., 2012). Limited nutrient applications across military landscapes, and the absence of stagnant surface water bodies within this area, may reduce the importance of nutrient water quality variables.

2.8 SWAT Description

SWAT was selected for application to the Kerr Brook watershed in this study. The rational for its selection is discussed in Section 4.1. SWAT is a culmination of decades of modelling efforts, incorporating aspects of various preceding models including GLEAMS, CREAMS, EPIC, QUAL2E and ROTO. Since its creation in the 1990s it has gone through a variety of improvements and spawned several independent adaptations (Gassman et al., 2007). While the majority of its development took place under the USDA Agricultural Research Service (ARS) and Texas A&M University, other US federal agencies have also made contributions. A detailed description of the SWAT model is given in its Theoretical Documentation Manual (Neitsch et al., 2011).

SWAT is being used throughout the US to support Total Daily Maximum Load analyses, research the effectiveness of conservation practices and perform macro-scale watershed assessments (Gassman et al., 2007). Applications of this model have also been expanding throughout the world including Europe, India, China, Africa, the Middle-East (Gassman et al., 2007) and Canada (Yang, W. et al., 2008; Wong et al., 2009; Yang, 2011; Gautam, 2012; Yang, 2012; Amon-Armah et al., 2013). This model is accepted around the world as a robust interdisciplinary watershed model, with hundreds of successful applications and related publications.

This model is semi-distributed and operates on a continuous daily time-step. It is generally applied at the basin-scale and structures landscapes into spatially distributed sub-basins. Within these sub-basins, lumped HRUs are defined by unique combinations of overlapping slope categories, LULC conditions and soil groups. Rainfall, temperature, relative humidity, wind speed and solar radiation may be used to drive model processes. These climate variables can be observed values or generated by the WXGEN weather generator model (Sharpley and Williams, 1990), and are assigned at the sub-basin level.

Surface runoff is computed with the SCS CN method or Green and Ampt Infiltration method from daily or hourly rainfall data. Rainfall intensity is estimated from the time of concentration and maximum monthly half-hour rainfall intensity. Rainfall may be stored in a single layer canopy before reaching the ground surface, at which point it is partitioned into surface runoff or the subsurface. Runoff partitioning methods can be influenced by soil moisture, slope and antecedent climate conditions. The peak runoff rate is determined from a modified rational formula, based on overland sheet flow and channel flow time of concentration.

Water percolates through the soil profile at a rate dependant on the saturated hydraulic conductivity and extent of saturation. If a soil layer is below field capacity water is accumulated in that layer. When field capacity is exceeded water may percolate to lower soil layers, enter the groundwater aquifer or contribute to lateral groundwater flow. Percolation and lateral groundwater flow rates are also dependant on other variables, such as hill slope gradient, hill slope length, soil depth and depth to impermeable layer. Percolation can be delayed before entering the shallow groundwater aquifer, which releases flow to the main channel with a recession model. Alternatively, water percolating from the soil profile can be partitioned to enter a deep aquifer which is lost from the system.

When water enters the main channel it is routed with the variable storage method (Williams, 1969) or Muskingum method (Overton, 1966). Channel velocity and depth is defined with Manning's equation for a trapezoidal channel of variable size. Each sub-basin only has one main channel reach for which flow routing is computed at the defined time-step. A floodplain of generic size is also fixed to each main channel reach.

Potential evapotranspiration can be calculated with the Penman-Monteith method, the Priestley-Taylor method or the Hargreaves method. Water is freely evaporated from canopy storage and transpired at a rate limited by the LAI. Evaporation from the soil can also be restricted from biomass and residual cover conditions. Actual ET is also affected by plant water demands. The distribution of ET demand across the soil profile is determined by a soil evaporation compensation factor (ESCO) and plant uptake compensation factor (EPCO).

Erosion is generated from surface runoff with the MUSLE, and eroded grain size distributions are estimated by empirical relations based on parent material properties. The runoff and sediments can then be routed through grassed waterways, vegetated filter strips, tributary channels and/or water impoundments before contributing to the main channel.

There are physically based approaches that can be used to enhance sediment routing methods and incorporate channel erosion processes. These stream power methods include the Simplified Bagnold model (Williams 1980), Kodoatie model (2000), Molinas and Wu model (2001) and the Yang sand and gravel model (Yang, 1996). Channel erosion rates are based on an erodibility factor and a cover factor. This erosion can be simulated to cause channel down cutting and widening.

Plant parameters can influence ET, erosion, runoff and many other watershed processes in SWAT. Plant growth, and their subsequent effects, is influenced by specie specific parameters. Water stress, temperature stress, nutrient stress and a variety of other factors can also contribute to processes linked to vegetation conditions.

2.9 SWAT Applications and Developments

SWAT can be used in a variety of methodologies to assess land-use change, climate change, management practices and more. There have also been many developments and modifications to the model structure to enhance its capabilities for specific situations. The capabilities of this model can be better appreciated knowing these methodologies, developments and specific applications.

There are several agricultural watersheds across Canada that are being studied and tested with the SWAT model. The Black Brook watershed, located in the potato belt of New Brunswick, has seen extensive study and SWAT applications (Yang, 2012; Yang, 2011). This 1,450 ha watershed consists of 25% forest, 10% roads, urban areas and streams, with the remainder composed of potato, barley and other agricultural crops. Yearly discharges have ranged from 5.1×10^6 m^3 in 2002, up to 11.4×10^6 m^3 in 1996, with total sediment loads ranging from 1526 tonnes yr^{-1} in 2002, to 8092 tonnes yr^{-1} in 1996. This calibrated model simulated monthly water and sediment yields with an R^2=0.91 and 0.5 and a NSE=0.88 and -0.29, respectively. Implementation of agricultural Best Management Practices (BMPs) in this model showed that annual guideline exceedance frequencies for TSS could be reduced by 23-25% (Yang, 2011), and maximum achievable annual sediment reduction of 89% could be achieved (Yang, 2012).

Thomas Brook is another watershed in Atlantic Canada that is being studied with SWAT to assess agricultural BMPs. This 784 ha watershed, located in Nova Scotia, has 57% crop coverage mostly composed of corn and small grains. Monthly stream flow simulations for the calibration and validation of this model achieved an R^2=0.9 and 0.73 and NSE=0.88 and 0.69, respectively. Monthly sediment simulations for the calibration and validation of this model achieved an R^2=0.66 and 0.48, and NSE=0.47 and 0.31, respectively (Amon-Armah et al., 2013).

SWAT has also been used to investigate different land cover scenario effects on water quality. One such study included the Raisin River basin in southeastern Ontario (Wong et al., 2009). This watershed covers

57,982 ha, with 19% forest cover, 19% wetlands and the remainder mostly pasture and agricultural crops. The analysis involved annual comparison of average flow, TSS concentrations and nutrient loads for six land cover scenarios. The modelling results and water quality parameters were used to forecast aquatic biodiversity and to develop achievable performance standards for flow regimes, sediments and nutrients. Simulated monthly average flows achieved a NSE = 0.84 and 0.86, and R^2 = 0.93 and 0.93, for calibration and validation, respectively. Limited sediment observations achieved a R^2 = 0.37, with mean daily concentrations of 2.68 mg L^{-1} and 2.69 mg L^{-1} for the calibrated and observed values, respectively.

Wetland conservation and restoration impact on water quantity and quality have also been studied with the SWAT model in Broughton's Creek, Manitoba (Yang, W. et al., 2008). This 25,139 ha watershed is composed of 71.8% agriculture, 10.8% range land, 9.5% wetland, 4% forest and 2.5% transportation. Different wetland conservation and restoration scenarios were examined, resulting in peak discharge reductions up to 23.4%, and annual sediment loading reductions up to 16.9% (approximately 50 tonnes yr^{-1}). Wetland storage volumes were estimated based on a linear relationship with wetland surface areas, while other parameters were adjusted during calibration. While there was limited observation data in this study, the model was judged to perform well.

SWAT has been assessed in forested watersheds for forest management applications. This has included research applications in Ontario (Guatam, 2012). Refinements to SWAT for these applications have included considerations of slope and aspect for solar radiation effects, incorporation of a litter layer, and anisotropic soil hydraulic conductivity. Refined wetland hydrology and upland-lowland HRU interactions have also been implemented (Watson, 2008). Improved forest growth modules have also been developed for forested watersheds due to limitations in the standard vegetation sub-models (Guatam, 2012).

The SCS CN, used in SWAT, implicitly assumes an infiltration-excess response to rainfall. In humid, well vegetated regions, and where soils are underlain by shallow restricting layers, runoff tends to be initiated by saturated soil according to VSA hydrology. The processes of VSA hydrology have been integrated into SWAT-VSA by using a topographic wetness index in HRU definition, as well as other minor adjustments (Easton et al., 2008). This background literature provided the foundation for model selection and preliminary data analysis required for this research.

3 Data Assembly and Preliminary Analysis

3.1 Site Description

Gagetown has been integral in the training of professional Canadian soldiers since it was established in the 1950s. The base includes more than 1,500 km of roads, 900 km of off-road tracks, 740 buildings and accommodates operations for more than 6,000 military and civilian personnel (Canadian Army, 2012). It is home to several major military establishments including operational units and schools for artillery, infantry and engineer service members.

The Range and Training Area (RTA) is located within Gagetown and covers most of the base. This area is used to conduct a variety of military operations, including tactical manoeuvres and live fire training exercises. The land was originally used for agriculture and forestry purposes before it was acquired by the Department of National Defence in 1953. Since then, more forested areas have been cleared to be used for training purposes; however, many deforested fields are overgrown by shrubs and other pioneer species, degrading their value for military training. Reclaiming and maintaining these open grasslands by grubbing operations, controlled burning, herbicide spraying and harvesting pose a significant challenge to land managers. These challenges pertain to resource allocation and logistical planning of such operations as well as environmental degradation concerns associated with these activities. Engineered roads provide transportation avenues throughout the RTA, while deforested grasslands provide areas where armoured vehicles and dismounted soldiers can conduct cross country manoeuvre operations. Repetitive off-road traffic has developed a vast network of distinguishable, un-engineered tracks, less obvious ruts and other land disturbances in these grassland areas. Vehicles also routinely traverse streams at designated fording locations during some operations. It is a concern that these activities and land management practices may be degrading aquatic habitats, soil health and vegetation cover within the RTA. These concerns are reflected in RTA management programs, such as the Sediment Erosion Control Plan and Aquatic

Management Plan. Land cover photographs and satellite imagery of LULC conditions in the RTA are included in Appendix B.

The RTA intersects a region between the Southern New Brunswick Uplands and the Maritime Lowlands, eco-region 121 and 122, respectively (Marshall et al., 1999). On average this area receives 885 mm of rainfall a year and 276 cm of snowfall, totalling 1,143 mm of annual precipitation. The daily average temperature is 5.3 $^{\circ}$C, which ranges from -9.8 $^{\circ}$C in January to 19.3 $^{\circ}$C in July (Marshall et al., 1999).

Most of the RTA is underlain by Paleozoic sedimentary rock with outcroppings of volcanic and plutonic rock in the southern regions. Soils generally consist of loam or gravelly sandy loam textures. Forests within the RTA account for approximately 66% of the land coverage. Other land cover includes barren and cleared stretches (6%), grasslands (18%) and aquatic environments (10%). Aquatic environments in the RTA include 44 ponds and lakes, 1,900 km of watercourses and 7,000 ha of wetlands (Estrada et al., 2012). Several benthic surveys have been conducted within the RTA to assess disturbance levels and habitat conditions, which are known to be occupied by several species at risk, including sensitive salmonid species (Estrada et al., 2012).

Kerr Brook is the focus watershed in this study, since it is highly disturbed and well documented with meteorological, GIS, hydrometric and water quality data. This 20 km^2 watershed is covered by approximately 26% mixed-forests, 32% grasslands, 36% brush lands including young pioneer species, and 4% barren features including roads, tracks and highly disturbed manoeuvre areas. Wetlands, beaver ponds and other water features are evident in this watershed but cover less than 2%.

3.2 Field Study

A field study assessment was conducted at 5 CDSB Gagetown during the summer of 2013. This provided an opportunity to gain a strong physical sense of the study areas and enabled the collection and compilation of selected data; however, most data used in this research were collected preceding this field study. Photographic documentations and qualitative stream surveys provided a general sense of the present watershed conditions. Support was given to stream monitoring efforts and corresponding data were considered in water quality analysis. Soil samples were also collected to enable the measurement of selected characteristics affecting soil erodibility. The scope and direction of this research were in preliminary stages of development during this field study so limited detailed data were collected. The ability to collect extensive hydrographic, water quality and GIS data over a finite survey period was also limited. Opportunities regarding enhanced, detailed and more targeted field studies are recommended in Section 6, considering the findings of this research.

3.3 Climate Data

Rainfall data are the primary driver behind all hydrological models. The majority of rainfall and climate data were provided by several meteorological stations that are operated within Gagetown by the Joint Meteorological Center. Hourly air temperature, relative humidity, wind speed, wind direction, precipitation, black globe temperature, atmospheric pressure and intermittent snow depths are recorded at these stations. Kerr Brook is in closest proximity to meteorological station REM02, with a Thiessen polygon coverage of 92%. No quality control or quality assurance data were available for these stations; however, selected rainfall events were compared against other stations in the area.

Meteorological station REM02 was the only station applied to the Kerr Brook watershed model. Climate data from 2007-2012 were used. This provided a two year model warm-up period followed by a simulation period from 2009-2012, concurrent with observed hydrometric and water quality data. Data gaps were backfilled, using other meteorological stations including: REM06, REM04 and Fredericton airport-Station A, in respective priority. Data were summarized on a daily time-step and integrated within the SWAT model. Hourly rainfall data were also used in the modelling analysis; however, model routing errors were encountered using this time-step so the typical daily time-step used in SWAT was used in this research.

Kerr Brook is located along the border of the Southern New Brunswick Uplands, eco-region 121, and the Maritime Lowlands, eco-region 122. This watershed is further divided between eco-district 499 and 506. Average historic climate norms for these districts are provided in Table 1 (Marshall et al., 1999).

SWAT incorporates the WXGEN weather generator model (Sharpley and Williams, 1990) to fill gaps in observed climate data or forecast climate trends. WXGEN input parameters were adjusted with Agriculture and Agri-Food Canada (AAFC) 1961-1990 climate norms (Marshall et al., 1999) or backfilled from United States Northern Maine station 183645, provided in the SWAT WGEN_US_COOP_1980_2010 database. Rainfall data gaps were limited and only overlap with observed hydrometric data during one day in December 2011 and eight days in November 2012.

Table 1. Eco-district 499 and 506 average climate norms from 1961-1990.

Month	Average PET (mm)	Average Daily Mean Air Temperature (°C)	Mean Daily Global Solar Radiation (MJ/m^2/day)	Rainfall (mm)	Snowfall (mm)	Total Precipitation (mm)
January	0.0	-8.6	5.45	46.5	58.3	103.3
February	0.0	-7.6	8.66	42.0	47.4	89.3
March	4.1	-2.1	12.48	51.0	40.5	92.1
April	41.0	4.1	15.22	70.2	16.9	87.7
May	78.6	10.2	18.20	100.2	1.0	100.9
June	106.8	15.3	20.01	90.3	0.0	90.4
July	117.9	18.3	19.82	90.0	0.0	90.0
August	101.7	17.6	17.38	94.9	0.0	95.2
September	65.8	13.1	13.26	98.2	0.0	98.1
October	32.9	7.8	8.59	99.9	1.3	101.3
November	7.5	2.0	4.98	105.3	14.9	120.3
December	0.0	-5.5	4.13	69.3	55.5	127.7
Annual Sum/Ave	556.3	5.4	12.3	957.6	235.8	1,195.9

3.4 Geographic Information Systems Data

GIS data are a critical component of many watershed models. For the SWAT models these data are primarily composed of a Digital Elevation Model (DEM), soil data and LULC data. The DEM is utilized to delineate the watershed, sub-basins, stream networks and slope categories. Soil, LULC and slope categories are overlaid to create unique HRUs. A 10 m DEM was utilized for this study, which was provided by the Gagetown GIS analyst cell. Soil data were originally taken from the AAFC soil survey database (Agriculture and Agri-Food Canada, 2012). LULC data were compiled from a variety of GIS inventories provided by the GIS analyst cell at Gagetown. All of this information was projected in NAD 1983 CSRS UTM Zone 19N. These GIS layers are displayed in Figure 9, along with the Kerr Brook watershed structure.

The DEM was clipped and filled within ArcGIS 10.0 in preparation for ArcSWAT processing. Inspection of wet area mapping data, derived from a one meter LiDAR DEM, indicated that some drainage areas were not accurately delineated. However, these areas were minimal compared to the entire study area and drainage areas appeared to be both over predicted and under predicted. For these reasons their influence was assumed to be negligible.

GIS soil data provided spatial delineation for common New Brunswick soil series at a scale of 1:126,720. These polygon features were converted into a 10 m raster format and projected into the DEM’s spatial reference. Limited soil data were provided along with this GIS; however, soil characteristics and parameters were supplemented by other sources discussed in Section 3.5.

The LULC input data required for ArcSWAT were compiled from a variety of sources and lumped into four categories; mixed forests (FRST), grasslands (RNGE), brush lands (RNGB) and barren areas (BARR). Minor LULC data inventories used in this classification were primary roads, tracks, wetlands and barren areas. The major land cover inventories within the study area included forests, grasslands and brush lands. These major categories remained relatively intact in this analysis. However, wetland riparian areas were merged into forests and all LULC categories took second priority to overlain barren areas. Bare areas were identified by a Colour Infrared Imagery classification in addition to road and track vector data. Roads and tracks were buffered to 6 and 3 m, respectively, converted to a raster format and merged with the bare soil data. Satellite imagery and ground level photography for these LULC categories is provided in Appendix B.

3.5 Soil and Geological Characteristics

There are three primary soil groups within the study areas: Tracy Loam (TRCL), Parleeville Gravelly Sandy Loam (PGSL); and Sunbury Gravelly Sandy Loam (SGSL). These soils cover 30%, 62% and 8% of the study areas respectively. Bedrock within Kerr Brook includes sedimentary rock to the northwest and volcanic rock to the south east. The general depth to bedrock is unknown but suspected to be shallow because of occasional rock outcroppings and bedrock streambeds in low river reaches. A detailed description of these soils is given below along with soil characteristics and parameters outlined in Appendix A.

Tracy Loams are a medium to coarse textured sandy loam and loam soils over a sandy loam, gravelly loam and sandy clay loam till. Drainage conditions are good except on level topography. Stones are common and drainage conditions are generally unrestricted (Wicklund and Langmaid, 1953). Depth to contrasting layer is greater than 100 cm but can range as low as 30 cm. This compact till is well drained with a medium textured upper horizon and medium to coarse gravelly-sandy loam parent material. C Horizon parent material has been classified as Hydrological Soil Group C with a saturated hydraulic conductivity between 0.5-10 mm hr^{-1} and an upper horizon depth between 40 cm and 80 cm (Fahmy et al., 2010). Site specific soil surveys have been conducted for these soils within Gagetown and were considered in this study (Castonguay and Arp, 2002).

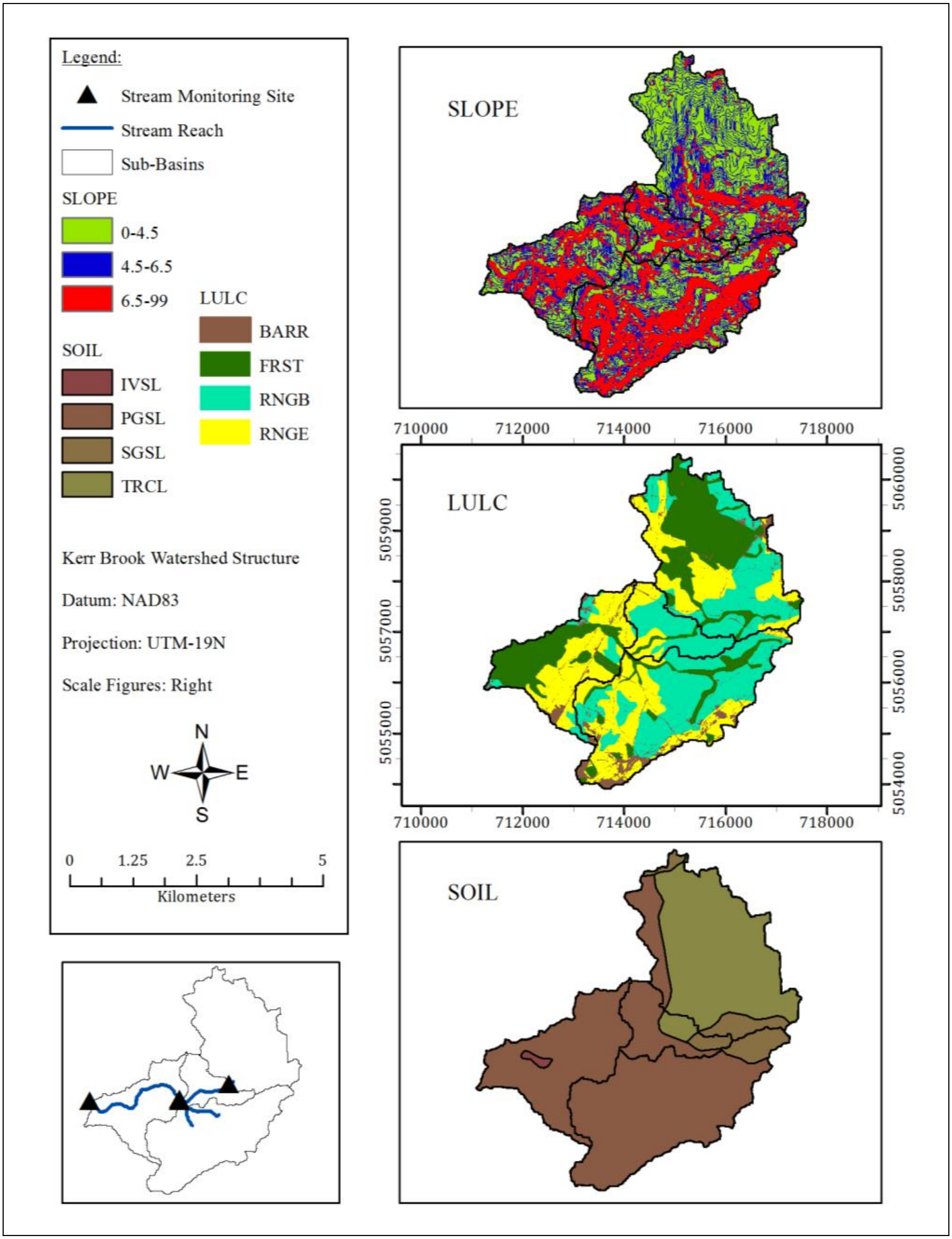


Figure 9. Kerr Brook HRU input layers and watershed structure.

Parleeville Gravelly Sandy Loams have a gravelly and stony nature with good to excessive drainage conditions. Rock outcrops occur frequently and till deposits may be shallow (Wicklund and Langmaid, 1953). Depth to contrasting layer is generally greater than 100 cm. C Horizon parent material has been classified as Hydrological Soil Group A with a saturated hydraulic conductivity between 50-100 mm hr^{-1} and an upper horizon between 28-53 cm (Fahmy et al., 2010). Site specific soil surveys have been conducted for these soils within Gagetown and were considered in this study (Castonguay and Arp, 2002).

Sunbury Gravelly Sandy Loams are frequently over shallow bedrock and rock outcrops are common. Soils are well drained with a coarse and stony texture (Wicklund and Langmaid, 1953; Colpitts et al., 1995). Depth to contrasting layer is generally greater than 100 cm and is well drained with a coarse to medium textured upper horizon and coarse parent material. C Horizon parent material has been classified as Hydrological Soil Group A, with a saturated hydraulic conductivity between 2-130 mm hr^{-1} and an upper horizon between 45 cm and 55 cm (Fahmy et al., 2010). Parameters for these soils were similar to those of Parleeville Gravelly Sandy Loam and because of the small area coverage of these soils in Kerr Brook, it was neglected in model development.

3.6 Hydrometric Data Analysis

Hydrometric data provides valuable calibration and validation information needed to develop and test hydrological models. The majority of stream flow data used in this study were collected by the Department of Fisheries and Oceans Canada (DFO). The spring, summer and fall seasons from 2009-2012 included the most comprehensive stream flow data set for downstream and upstream monitoring locations in Kerr Brook, displayed in Figure 9. A midstream monitoring station was also used in this study area; however, limited data were available for this location. Hourly stream stage was measured with a pressure transducer data logger at both locations. Discharge was measured at eight different times for the 2009-2012 data set, ranging from 0.009-1.743 $m^3 s^{-1}$ for the downstream location and 0.012-0.927 m^3

s^{-1} for the upstream location. Transducer elevations were measured and manually verified four times in 2009, twice in 2011 and once in 2012. Manual water level measurements and transducer depth differences varied from 0.000-0.069 m. Flow depth and velocity measurements were made at 20 cm intervals to compute instantaneous stream discharge. Each discharge was measured at three locations in proximity to the pressure transducer pad and averaged. Stage-discharge lookup tables were constructed, including HEC-RAS modelling, by DFO personnel and applied throughout the study period. Hydrographic data are summarized in Appendix C.

These data are assumed to be accurate and reasonable; however, uncertainty in high flow measurements may be significant due to a lack of high discharge measurements. Vegetation, backwater effects, hysteresis and changes in stream cross-sections are assumed to have negligible influence on stage-discharge relations; however, there was insufficient quantitative data to validate these assumptions.

Flow duration curves were constructed for the upstream and downstream Kerr Brook stations, as recommended by Helsel and Hirsch (2002). All observations, over inconsistent intervals from 2009-2012, were used. This is a relatively short timeframe to provide insight into high flow frequencies; however, these data provided a good sense of low and mid-flow regimes. These curves were used to help define an approximate event-flow threshold, identified by a significant change of slope in these curves. Upstream and downstream flow durations curves are included in Appendix C. These flow duration curves were constructed with the Weibull plotting position formula, given below:

$$P_f = \frac{i}{(n+1)} \qquad [\ 16\ ]$$

In Equation [16], P_f is the probability of exceedance of observation i, n is the total number of observations and i is the observation number arranged in descending order, where the highest observed flow is observation i=1.

A baseflow filter was used to split stream flow into surface flow and groundwater flow for manual calibration, as recommended by Arnold et al. (2012). Surface erosion is driven by surface runoff making it a critical target for calibration. However, these filter parameters are subjective and were based on literature, geological conditions and graphical baseflow separation results, adding additional uncertainty. A two parameter digital filter was selected for this analysis as given below:

$$b_t = \frac{(1 - BFI_{max})ab_{(t-1)} + (1 - a)BFI_{max}y_t}{1 - aBFI_{max}} \qquad [\ 17\ ]$$

In Equation [17], BFI_{max} is the maximum baseflow index (the long-term ratio of baseflow to total stream flow), a corresponds to the groundwater recession constant, $b_{(k-1)}$ is the baseflow at time k-1 and y_k is the total stream flow at time k (Eckhardt, 2005).

Within this study area, groundwater reservoirs were conceptualised as a porous shallow soil aquifer underlain by a hard rock aquifer. Two sets of filter parameters were used in the baseflow separation procedure. In one case, the hard rock aquifer was neglected and the shallow aquifer was assumed to contribute significant and rapid baseflow contributions after rainfall events (shallow aquifer parameters: BFI_{max}=0.65 and a=0.97). The second case assumed that hard rock aquifer contributions were lost from the system and integrated two baseflow filter iterations to isolate hard rock aquifer contributions and shallow soil contributions (shallow aquifer parameters: BFI_{max}=0.75 and a=0.925; and hard rock aquifer parameters: BFI_{max}=0.2 and a=0.955). These filter parameters are supported by Eckhardt (2005); however, this multi-component separation method has not been validated in any literature. Simulating multiple groundwater reservoirs, as described here, is outside the capabilities of the SWAT model. Application and further consideration of this baseflow separation method are discussed in Section 4.4. Graphical results from this baseflow filter analysis are summarized in Appendix C.

3.7 Water Quality Analysis

3.7.1 Water Quality Conditions

Poor water quality conditions have been observed throughout the Gagetown RTA (Hood, 2013). A water quality analysis was conducted to acquire a general indication of conditions observed in Kerr Brook. Water quality criteria and evaluation methods are discussed in Section 2.7. The CCME WQI was utilized for this analysis (CCME, 2001). NAESI-IPS guidelines were considered for TSS and turbidity and CCME CEQG for pH. Average and median daily TSS concentrations in excess of 6.1 mg L^{-1} were considered a failure. Average and median daily turbidity in excess of 2.8 NTU were also considered a failure (Culp et al., 2009). An average daily temperature threshold of 24 $^{\circ}$C and an acceptable average daily pH range of 6.5-9 were also utilized (Raleigh, 1982; CCME, 1996). Turbidity, temperature and pH data were collected with a YSI multi-meter over four semi-continuous monitoring years. TSS data were generated with the regression analysis discussed in Section 3.7.2. Daily median and average values were compared, along with data trimmed by the mirrored 5th percentile. Conceptual water quality variables were also considered in this analysis to evaluate the effect of additional water quality parameters, with the assumption these conceptual variables pass criteria at all times.

Water quality conditions in Kerr Brook are suspected to be marginal, with a WQI ranging from 48-57. This lower range was established from average daily observations. The upper range was established from median daily turbidity, average daily TSS and all data trimmed at the mirrored 5^{th} percentile. Other water quality variables are suspected to be of good condition in Kerr Brook. With limited anthropogenic sources to affect many water quality variables, such as metals and nutrients, this assumption seems realistic. The addition of one extra water quality variable, assumed to pass criteria at all times, improved the WQI by about 8 points. This creates the potential that water quality conditions may actually be fair. The majority of poor water quality variables were also caused from runoff events, which may cause misleading results, as the WQI is more designed for steady state flow conditions. WQI results and a summary worksheet are available in Appendix D.

Vehicle water crossing operations have the potential to impair water quality in local streams. Analysis of grab samples collected downstream of crossings indicate that this activity can be responsible for turbidity and TSS loadings as high as 1,000 NTU and 1,000 mg L^{-1}, respectively, immediately downstream of crossing sites. However, daily vehicle loads were not observed to significantly affect water quality at the watershed outlet; daily turbidity statistics were not strongly correlated to daily vehicle loads. Filtering data from potential runoff events and turbidity outliers did not significantly improve any correlation. The only mild correlation was observed for the maximum daily turbidity for the upstream monitoring location ($r = 0.22$). Potential point source contributions from vehicle stream crossing activities were neglected in modelling efforts because of this lack of correlation. A summary of this analysis is given in Appendix D.

3.7.2 Sediment Yield Regression Analysis

Regression models are commonly utilized to predict stream sediment yields from regressor variables, such as turbidity and stream flow (Helsel and Hirsch, 2002; Rasmussen et al., 2011). Turbidity is a measure of water clarity and can be a statistically significant indicator of TSS concentrations. However, turbidity can also be affected by other aquatic conditions, such as dissolved matter, colour and plankton. Stream flow also affects sediments, providing transport energy to erode and suspend particles. All these parameters have site specific characteristics and required case-by-case analysis to develop reliable regression models.

Over the past eight years 77 turbidity and TSS samples were collected during eight partial runoff events, including 41 concurrent flow measurements at the downstream Kerr Brook monitoring location. These data were used to create an event-based sediment yield regression model. This model was applied to periods of continuous monitoring to provide an approximate daily sediment yield to compare against simulated results. Additional data, besides turbidity and flow, suspected to affect sediment yields were also analysed. These additional parameters included days since last runoff event, cumulative vehicle activity since last runoff event and rising/falling hydrograph limb. Among these regressor variables, the most effective equation for the downstream monitoring station was selected, given in Equation [18]:

$$TSS = 2.61 + 0.41 \cdot T + 18.00 \cdot Q \qquad [\ 18\ ]$$

Where TSS is hourly total suspended solids concentration (mg L^{-1}), T is turbidity (NTU) and Q is discharge (m^3 s^{-1}). The adjusted R^2 for this model is 0.61 with a standard error of 41.5%. T-stats and α values were 0.20 and 0.84, 2.75 and 0.01, and 4.6 and 0.00 for the intercept, turbidity and flow variables, respectively. The intercept was not statistically significant so TSS was set to zero for zero turbidity values. This is also more physically realistic because clear water is not likely transporting sediments in a natural environment. This equation was applied in two iterations: for all flow conditions; and for flows above 0.35 m^3 s^{-1}, which was the 20% flow exceedance probability. Applying this model exclusively to high flow conditions reduced average predicted sediment yields by about 2% each year. Sediment yield results derived from this regression equation are summarized in

Table 2.

Monthly suspended sediment yields predicted with this method range from 0 tonnes for dry summer months, to 150 tonnes for late spring and early summer months and up to 380 tonnes in the fall. It is suspected that significant spring freshet events were not included in the data utilized in this analysis. Uncertainty associated with this analysis may be substantial. One aspect of this uncertainty was quantified by the 90% confidence interval from the regression analysis, resulting in annual prediction differences ranging up to 80% when significant yields were predicted. Other sources of uncertainty may also be apparent in this analysis, such as the influence of antecedent conditions, shifting fluvial geomorphologic conditions and military training activities.

Contrary to typical conditions, stream flow was a more effective predictor for TSS than turbidity, with a single linear regression model adjusted R^2 of 0.54 compared to 0.24. This may be from sampling error, such as oversampling bedload particles. Most samples were drawn from 30 cm above the stream bed from an ISCO auto-sampler intake. There were also 78 turbidity observations, as oppose to 41 flow observations, which may have added additional variability in the turbidity regression model.

Multiple Linear Regression (MLR) of flow and turbidity improved model statistics, with an adjusted R^2 of 0.61. Additional parameters proved to be insignificant and not within an acceptable confidence interval ($\alpha > 0.1$ and t-Stat < 1.3). Missing flow data were simulated with a HEC-HMS model in order to utilize additional turbidity and TSS data. This model was calibrated with Fall 2010 data (NSE = 0.93) and validated with 2009 and 2011 Fall data (NSE = 0.74) from a previous hydrology project (Burdett, 2013). However, simulated flows seemed unrealistic and did not improve the regression analysis. There was no significant pattern in the model's residuals so variable transformations were not conducted. This regression analysis is summarized in Appendix E.

There are several issues that should be addressed for this regression analysis. Firstly, the potential issue of multicollinearity, where independent regression variables are themselves highly correlated, can be problematic. Turbidity and stream flow may be highly correlated, for example. In this case, turbidity and stream flow had an observed correlation coefficient of 0.57 (< 0.95) and were deemed appropriate for use in MLR (Rasmussen et al., 2011). Another concern is the independence of observed data. It can be argued that intra-event observations are dependant, violating a fundamental requirement of linear regression analysis. This can be observed to some degree in Appendix E, where individual events exhibit a distinct pattern of observations. It would be preferable to utilize event mean concentrations as single observations; however, all data were used independently due to data limitations. Future monitoring programs may well provide sufficient event monitoring information to support a revised regression analysis utilizing event mean concentrations. Model stationarity is also a potential issue, such as seasonal effects and bias due to most data being collected during the fall. This model is also suspected to underestimate sediment yields from high flow events. Data may be biased towards small and medium flow events and large flow events tend to dominate erosion processes (Wigmosta et al., 2007). All these issues contribute a degree of uncertainty in the application of this model and demonstrate opportunity for improvement.

Table 2. Downstream suspended sediment yield regression results.

Observation Year	Month	Sediment Yield (t)	Upper 90% Confidence Yield (t)	Lower 90% Confidence Yield (t)
2009	August	149	228	72
2009	September	24	40	9
2009	October	201	328	80
2009	November	39	74	10
2010	May	3	7	0
2010	June	34	61	10
2010	July	1	2	0
2010	August	0	0	0
2010	September	0	0	0
2010	October	19	39	4
2010	November	321	509	138
2011	May	125	218	40
2011	June	9	20	2
2011	July	17	34	4
2011	August	131	211	56
2011	September	0	2	0
2011	October	28	54	8
2011	November	14	36	1
2012	June	3	8	0
2012	July	57	92	23
2012	August	0	1	0
2012	September	65	111	23
2012	October	75	133	24

A regression analysis for the upstream monitoring location was also conducted based on 36 observations from six partial runoff events. Turbidity alone appeared to be the best predictor variable for this location with an adjusted R^2 of 0.59 for Equation [19], displayed below:

$$TSS = 1.41(T) - 0.81 \quad [\ 19\ ]$$

Again, this equation was applied in two iterations: for all flow conditions; and for flows above 0.15 $m^3\ s^{-1}$, which was the 20% flow exceedance probability.

Sediment data from this regression analysis were used as a comparative value for SWAT sediment yield simulations. This unconventional approach may be subject to criticism because it involved comparing results of one model to another. Using measured TSS values for the limited number of observed days was another potential approach considered in this situation. One issue with this, however, was that no observed event included a full 24 hours of monitoring, so no daily sediment yields were actually observed. Daily regression analysis could be used for individual events to make a compromise between these two approaches. This method is also likely to improve the regression model accuracy. However, this would still necessitate comparing one model to another, and there would be substantially fewer estimated regression values for comparison. Despite the limitations with this regression approach discussed above, the selected method was judged to be the most effective means to approximate watershed sediments yields with available data. Managing cumulative watershed sediment effects is a demanding process and can require up to 10 years of pre- and post-development data (National Council for Air and Stream Improvements, 1999). Such an extensive data set is, at this time, both unavailable and outside the scope of this study.

3.7.3 Temperature Regression Model

With stream temperature guideline exceedance being a concern in Gagetown (Hood, 2013), general trends in observed temperature data were compared with the water temperature sub-model used in SWAT. SWAT utilizes the following regression model to predict in-stream water temperatures:

$$T_{water} = 5.0 + 0.75T_{av} \qquad [\ 20\ ]$$

In Equation [20], T_{water} is the mean daily water temperature (°C) and T_{av} is the mean daily air temperature (°C) (Neitsch et al., 2011). A regression analysis of in-stream temperature data from the downstream Kerr Brook monitoring station and air temperature from meteorological station REM02 resulted in similar results, given in Equation [21] below:

$$T_{water} = 4.99 + 0.77T_{av} \quad [21]$$

This model achieved an R^2 of 0.78 and all terms were significant (P-value < 0.01). Generally, average daily water temperatures of 21.3 °C imply maximum water temperatures above 24 °C 50% of the time. For this study area, the SWAT temperature model is adequate at predicting stream temperatures within Kerr Brook. However, there are no opportunities in the SWAT model framework to explore land cover and riparian effects on stream water temperature.

4 Model Development

4.1 Model Selection

Appropriate model selection is an important aspect of any environmental simulation project. The purpose of this study was to simulate and understand the impact of military landscapes on hydrology and water quality conditions at Gagetown. Model selection was designed to make optimal use of available stream, climate and GIS data. There are a variety of models which are potentially appropriate for military land managers; however, they vary in data requirements and intended use. Models also require unique input and validation data in order to instill confidence in the model's performance.

The new generation of erosion models focus on highly distributed, 2-D flow routing capabilities requiring substantial amounts of input data for field-scale applications. Surface runoff is of prime importance in these models and other components of the hydrologic cycle are not always considered. The processes these models simulate are more physically-based than other 1-D, lumped approaches and have enhanced ability to predict distributed overland flow, sediment transport and deposition. These types of models can also include detailed road hydrology, soil mechanics and vegetation dynamics. At a large landscape or basin scale, these models become increasingly cumbersome to apply. However, they could be highly valuable if applied within a multi-spatial scale approach where these detailed models are only utilized on hillslopes or small watersheds identified by larger scale, lumped models.

The unique impact of off-road vehicle manoeuvres is suspected to have a significant influence on surface runoff and erosion patterns. Ruts and tracks are localized areas of reduced infiltration, and susceptible to extended periods of surface ponding. Ruts and tracks are also barren features susceptible to accelerated erosion rates; however, the soils are generally compact which may also limit erosion rates. These features act as flow accumulation channels which may accelerate runoff travel time, increase sediment transport, and reduce the effectiveness of vegetated filter strips. These physical characteristics of tracks, ruts and manoeuvre ground are displayed in Appendix B. Even the complex, highly distributed models discussed above have limited ability to simulate all these potential effects. Also, at the landscape and basin scale these processes may have negligible influence.

With Gagetown covering over 1,100 km^2, models that can be effectively applied to large areas were preferable. Continuous streamflow data for calibration and validation, also gave preference to continuous hydrological models as oppose to event-based or stochastic climate models. SWAT, DHSVM and HSPF are well supported and commonly applied hydrology models meeting this criteria. Water quality components are also integrated into these models. HSPF is commonly reported to require substantial parameterization efforts and is not generally considered to be user-friendly (Beckers et al., 2009). DHSVM is not widely utilized and is limited by a difficult user interface (Beckers et al., 2009). SWAT, on the other hand, has a relatively straightforward user-interface and is integrated within a GIS framework. It was designed for application in large, ungauged agricultural watersheds requiring minimal parameterization (Neitsch et al., 2011). This model is publically available, there is a strong user community and it is widely applied for both research and practical applications around the world, as discussed in Section 2.9.

SWAT was selected for this study because of its capacity to effectively process and simulate lumped hydrological and erosion processes. There is sufficient and appropriate data to calibrate and validate predictions. GIS data are also available and easily integrated in this semi-distributed model. Erosion and overland flow processes may be simplified in this model; however, these simplifications make large scale applications efficient even though this may sacrifice some accuracy and precision. SWAT operates on a daily time-step and has a strong capacity to process decades of data. This time-step will be effective to simulate landscape hydrological processes but will limit the ability to predict detailed hydrographic data.

4.2 Watershed Structure

The Kerr Brook SWAT model was delineated within ArcSWAT utilizing GIS data discussed in Section 3.4. Rivers were defined at a 66 ha contributing area resolution, with the watershed outlet located at the downstream monitoring station. The upstream monitoring location was used to delineate one sub-basin. Two other sub-basins were defined to isolate a hilly tributary to the south east and an intermittent mid-stream monitoring location. HRUs were defined with a 20% soil cover threshold and 20% slope cover threshold. A 1% land cover threshold was selected to adequately represent barren areas, which is substantially smaller than the common recommendation of 20% (Winchell et al., 2007). These geographic characteristics are summarized in Table 3 and Figure 9.

Table 3. Sub-basin geographic parameters (% coverage).

Sub-Basin	Area (ha)	LULC (%) FRST/RNGE/RNGB/BARR	Soils (%) TRCL/PGSL	Slope (%) 0-4.5/4.5-6.5/6.5-99
SB1	721	39 / 24 / 33 / 4	93 / 7	51 / 36 / 13
SB2	172	6 / 28 / 65 / 1	21 / 79	26 / 44 / 30
SB3	687	11 / 33 / 48 / 8	0 / 100	29 / 56 / 15
SB4	403	38 / 45 / 10 / 7	0 / 100	33 / 36 / 31

4.3 Input Parameter Development

Establishing reasonable parameters to initiate model simulations can greatly enhance calibration efforts and improve the uniqueness of a particular watershed model. Initial parameters are outlined in Appendix A, along with brief explanatory remarks. Physically based parameters, and those commonly reported as sensitive in the literature, received the most attention. Some parameters were adjusted based upon qualitative knowledge of the watershed's hydrology and others were default values. Parameter values reported in the literature were also considered during initial parameter assignment.

SCS CNs were judged based on qualitative land cover conditions. Good forest conditions were assumed at first because most forests are relatively undisturbed. Grasslands were defined as poor due to cross country vehicle manoeuvres, causing soil compaction and vegetation disturbances. Brush lands were judged as fair due to only occasional vehicle disturbances. Brush lands also include pioneer tree species and at time can be well vegetated. Lastly, barren areas were defined based on a combination of bare soil fallow and unpaved roads. These conditions, combined with hydrological soil group parameters discussed in Section 3.5, drove the assignment of SCS CNs, a parameter commonly reported as sensitive (Arnold et al., 2012).

The small size of the watershed and flashy hydrograph response required that many flow timing parameters to be adjusted accordingly. This flashy characteristic is described by a rapid response to a rainfall event, where the difference in magnitude between storm event response flow and baseflow conditions is significant. This included minimizing default parameters, such as SURLAG and GW_DELAY, while maximizing parameters, such as ALPHA_BF.

Features including vegetated filter strips, grassed waterways and wetlands were not included in the initial model. However, these features were considered during the sensitivity analysis and model calibration. There are limited data available to physically characterize these features in this model. Additional field surveys may be valuable to help better define these features.

The USLE C-factor is one parameter that is subject to significant uncertainty in this initial parameter assignment. Grasslands and brush lands are two land cover categories well documented in the literature (Wall et al., 2002). However, how these land cover conditions are affected by military training operations is not well documented. Some studies on military training ground have reported cover factors but regional variability, including many factors, may significantly affect these values for application to Gagetown (Warren et al. 1989; Liu et al., 2007; Dalton, 2008; Gaffer et al., 2008). Bare soil transect surveys in Gagetown were used to guide cover parameters, including literature values. These land cover categories indicated that exposed bare soils may account for approximately 9% and 4% of grasslands and brush lands, respectively. As discussed in Section 2.5, many different methods have been used to estimate

C-factors for military lands. A more focused GIS approach, combined with a field survey quality control element, is expected to greatly improve the lumped cover factors used in this study.

4.4 Calibration and Uncertainty Analysis

Model calibration was conducted to enhance predictive accuracy by refining parameters, within reasonable and logical constraints, to match observations. Complex hydrological and water quality models demand careful consideration during calibration and uncertainty analysis. Watershed models have become increasingly popular to assess land management strategies, land-use change and pollutant control. The demand to increase the accuracy of these models and better quantify their associated uncertainty has also increased (Yang, J. et al., 2008). Over parameterization, non-uniqueness of solutions, data limitations and uncertainty are common issues that plague the development of reliable watershed models (Abbaspour et al., 2007; Govers, 2011; Jetten and Maneta, 2011; Arnold et al., 2012).

There are a variety of approaches and methods used to assess input sensitivity, calibrate parameters, quantify output uncertainty and validate watershed models. There is no standard procedure among these approaches. Some approaches may be more effective than others, but this may depend upon the user, the model structure, data availability and the intended application of the model. These procedures, as utilized in many studies, often lack clear documentation (Engel et al., 2007). This issue has been identified as an area of improvement for future reporting to enable readers to more effectively interpret results (Tuppad et al., 2011).

Widely applied calibration and uncertainty analysis methods were used to calibrate hydrological parameters to observed stream flow conditions for the Kerr Brook SWAT model. Sediment parameters were not calibrated due to the lack of observed sediment yield data, but compared to the TSS regression model, discussed in Section 3.7.2. The sensitivity, calibration and validation procedure used in this research followed four steps. These four steps included: 1) manual sensitivity analysis and model familiarization; 2) automated sensitivity analysis and calibration; 3) manual calibration; and 4) final automated calibration. These steps are integrated into a model development flowchart, displayed in Figure 10. An iterative approach was used to consider upstream and downstream observed data, but more focus was given to downstream calibration.

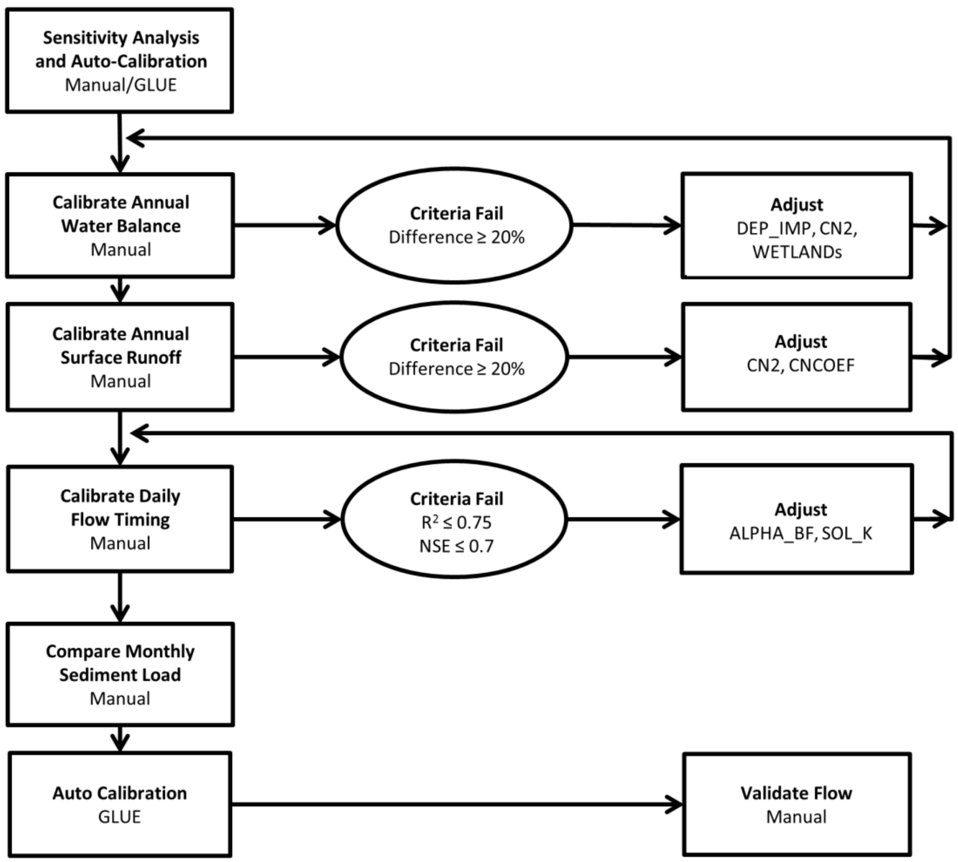


Figure 10. Sensitivity, calibration and validation flowchart.

Observation data were split into two sets for calibration and validation. Observed water years selected for calibration were 2010 and 2011. These years were selected because the 2009/2012 and 2010/2011 water years demonstrated similar rainfall statistics, such as total observed rainfall, peak daily rainfall, number of dry days and average rain per day. Parameters affecting winter hydrological processes were not included in calibration. There were occasional snow fall events during the observed data periods; however, these events were few and negligible.

Suspended sediment yields, the water quality parameter of prime interest, was only compared to regression model results. However, select sediment parameters were adjusted during the sensitivity analysis and after manual calibration to assess their general influence on sediment yield simulations. This included parameters, such as cover-factors, soil erodibility, slope-length factors and vegetated filter strips.

4.4.1 Manual Sensitivity Analysis and Model Familiarization

The manual sensitivity analysis and model familiarization procedure involved running SWAT with default or preliminary input parameters. These parameters were generally grouped by process and varied from their maximum to minimum values, followed by a graphical comparison of results. Output results, such as stream flow, soil water storage, wetland storage, LAI and groundwater flow, were qualitatively assessed. This first step was designed to be mostly qualitative and educational. For more experienced SWAT users, and hydrological modellers, this step may be unnecessary. However, new user and practitioners should not overlook such a step.

4.4.2 Automated Sensitivity Analysis and Calibration

The initial automated sensitivity analysis and calibration was conducted for two reasons; 1) to automate a more robust sensitivity analysis; and 2) to assess automated calibration as a standalone process. Assessing parameter sensitivity and calibrating complex hydrological models can be difficult, monotonous and time consuming. Automated calibration programs are becoming increasingly popular and capable to effectively assess parameter sensitivity and calibrate model parameters. SWAT - Calibration and Uncertainty Program (CUP), was used in this study, which is a publicly available program that integrates several automated calibration and uncertainty methods with SWAT input/output files. The Generalized Likelihood Uncertainty Estimation (GLUE) method was used in initial and final calibration efforts to assess its ability to improve model predictions. The Sequential Uncertainty Fitting (SUFI2) method was also considered in auto-calibration trials but GLUE tended to provide more realistic parameter adjustments and has a more simplistic methodology for practical management application. One negative aspect of GLUE is that it required more time for additional simulations runs.

The GLUE and SUFI2 analysis is assessed by a P-factor term, which accounts for the percentage of measured data bracketed by the 2.5% and 97.5% level of the cumulative distribution of the output variable, the 95PPU. The strength of this P-factor is then assessed by an R-factor, which is the thickness of the 95PPU band divided by the standard deviation of measured data. A P-factor of one and an R-factor of zero represent a perfect fit, while a P-factor of 0.8-1.0 and an R-factor less than one is generally desirable. However, a high P-factor can be achieved at the expense of a high R-factor and vice versa.

The GLUE procedure is a Monte Carlo method, which commences by sampling parameter set distributions, usually more than 5,000. These sets are assessed as behavioral or non-behavioral by a likelihood measurement threshold, generally the NSE. Behavioural parameters are given a likelihood weight against the total number of behavioral parameter sets. The final prediction uncertainty is given as the prediction quantile from the cumulative distribution realized from the weighted behavioral parameter sets. Further discussion and applications concerning GLUE are provided by Beven and Binley (1992), Blasone et al. (2008), Yang, J. et al. (2008) and Abbaspour (2012).

Parameters included in this automated process were commonly reported as sensitive in the literature (Arnold et al., 2012) and those identified during manual sensitivity analysis. These parameters, along with their initial and final ranges, are outlined in Appendix F. Parameter ranges were assigned based on realistic values for a variety of conditions. Two iterations were conducted with GLUE, including 10,000 simulations each. NSE objective function thresholds of 0.65 and 0.75 were defined for the first and second iteration, respectively. Downstream flow was considered for the first iteration and both upstream and downstream flows were considered for the second. The objective function weights of upstream and downstream observations were equal in this analysis.

4.4.3 Manual Calibration

Manual calibration included multiple iterative steps outlined in Figure 10. This manual calibration first sought to balance total water yields, surface runoff and groundwater flow by a percentage difference criteria from annual observed data. Runoff was separated from total flow through application of a baseflow filter, as discussed in Section 3.6. A summary of manual calibration results and parameter adjustments are provided in Appendix G.

During manual calibration, a water balance approach was conducted using a percent difference statistic, given in Equation [22], for annual observation periods. The correlation coefficient (R^2, Equation [23]) and Nash Sutcliffe Efficiency (NSE, Equation [24]) statistics were also used for daily results, summarized annually. These two statistical criteria are the most widely utilized in hydrological modelling (Arnold et al., 2012).

$$\%d = \frac{\sum Q_{m,i} - \sum Q_{s,i}}{\sum Q_{m,i}} \qquad [\ 22\ ]$$

$$R^2 = \frac{\left[\sum(Q_{m,i} - \bar{Q}_m)(Q_{s,i} - \bar{Q}_s)\right]^2}{\sum(Q_{m,i} - \bar{Q}_m)^2 \cdot \sum(Q_{s,i} - \bar{Q}_s)^2} \qquad [\ 23\ ]$$

$$NSE = 1 - \frac{\sum(Q_{m,i} - Q_{s,i})^2}{\sum(Q_{m,i} - \bar{Q}_m)^2} \qquad [\ 24\ ]$$

Equations [22], [23] and [24], where $Q_{m,i}$ is the measured flow on day i ($m^3\ s^{-1}$), $Q_{s,i}$ is the simulated flow on day i ($m^3\ s^{-1}$), $\bar{Q}_m$ is the average measured daily flow ($m^3\ s^{-1}$) and $\bar{Q}_s$ is the average simulated daily flow ($m^3\ s^{-1}$).

Two iterations were conducted with different baseflow filter parameters. One iteration utilized filter parameters recommended for ephemeral streams with a porous aquifer, BFI_{max} = 0.65 and a = 0.97 (Eckhardt, 2005). Another filter approach applied two baseflow components: one for a perennial stream with a porous aquifer, BFI_{max} = 0.75 and a = 0.925, and another for a perennial stream with hard rock aquifer, BFI_{max} = 0.25 and a = 0.955 (Eckhardt, 2005). Graphical separation of selected stream hydrograph events, using a linear semi-logarithmic approach, agreed most with parameters for a perennial stream with a porous aquifer. Even though these filter parameters are subjective, this method was the most appropriate separation approach, considering available data. This type of separation exercise is also recommended during model development (Arnold et al., 2012). Separation results are summarized in Table 4. The separation approach considering two baseflow components was used to adjust daily observed flows. The hard rock aquifer baseflow component was conceptualised to be equivalent to deep aquifer recharge, such that the flow was lost to the system in SWAT. This baseflow component was subtracted from daily observed flow to remove its influence on calibration statistics. Water balance was achieved by comparing deep aquifer recharge and this hard rock baseflow component over the observed periods. Graphical results from these two baseflow filter approaches are included in Appendix C.

Parameters were first adjusted to achieve acceptable total water yield criteria, compared to observed discharge. After this, simulated water balance components were compared to the baseflow separation values, including surface runoff, shallow aquifer recharge and deep aquifer recharge. These were also assessed with the percent difference criteria for each annual observation period. After this, criteria shifted to focus on timing and peak flow parameters, utilizing daily flow optimization statistics with R^2 and NSE.

Table 4. Annual observed water balance targets from baseflow separation.

Year	**Baseflow Components**	**Precipitation (mm)**	**Surface Runoff (mm)**	**Groundwater (mm)**	**Deep Aquifer Recharge (mm)**
2009	Single	564	170	95	-
2009	Double		129	92	44
2010	Single	792	169	75	-
2010	Double		121	84	38
2011	Single	807	180	106	-
2011	Double		135	100	51
2012	Single	711	115	50	-
2012	Double		86	54	25

Rainfall conditions were also evaluated over select periods to explore potential error and variability in their observed values and resultant simulation effects. The dates and rain gauge values considered are outlined in Table 5. Maximum and minimum rainfall values were integrated into simulations. All of these gauges are located no more than 15 km from the study area. As illustrated in Table 5, daily rainfall volumes varied up to 50%, or 30 mm, for some of these events.

Table 5. Select dates and variable rain gauge data (mm rainfall).

Date / Met Station	REM02	REM06	REM04
8/28/2011	91	81	66
11/5/2010	70	44	39
11/7/2010	29	29	39
11/8/2010	43	29	50
11/9/2010	28	24	35
8/29/2009	50	48	38
8/30/2009	19	23	20
11/17/2010	28	16	20
7/22/2010	58	40	29

Sediment yields were only compared to TSS regression model results, as mentioned previously. There was limited observed sediment data and information to support confident parameterization of sediment production and reduction variables. No channel aggradation or degradation was simulated, nor were sediment transport coefficients altered. Again, there was limited data to support confident parameterization of these processes and no meaningful way to objectively identify different sediment source components. Suspended sediments, used in the regression model, are typically controlled by watershed production rates (Lord et al., 2009) and so may be less affected by channel and deposition processes. There are other sources and activities that can affect sediment yields not considered in this study. Herbicide spraying, control burning, road construction and road maintenance are all activities that are recognized to cause erosion and sedimentation issues in military training areas (Donigian et al., 2010). The MUSLE is limited by its inability to account for sub-daily and even daily erosion rates due to the fact that the USLE was only developed to provide annual estimates (Jeong et al., 2010). It is also limited in its ability to account for the second storm effect and other temporally variable erosion processes (Arnold et al., 2012). Many erosion models also lack the ability to simulate the dominance of large storm events on long-term sediment yields (Wigmosta et al., 2007; Nearing and Hairsine, 2011). These complexities and limitations provide significant opportunities for advancement in observed sediment data and model simulations.

4.4.4 Final Automated Calibration

Final automated calibration with GLUE followed procedures similar to that in the initial sensitivity and calibration analysis. Two iterations were conducted: one considering downstream flow and a NSE threshold of 0.80; and another considering both upstream and downstream flows with a NSE threshold of 0.80. Select parameters from the manually calibrated model were incorporated into the final automated procedure. Fewer parameters were considered and parameter ranges were smaller, compared to the initial analysis. These parameters and parameter ranges were selected based on knowledge gained from pervious steps, such a parameter sensitivity and watershed characteristics. CNs and soil percolation (DEP_IMP) parameters were lumped when considering downstream observations. When considering upstream and downstream observations, these two parameters were disaggregated based on their underlying soil conditions. The upstream and downstream drainage basins' dominant soil groups were different so this provided more flexibility to match upstream and downstream observed values. Manual calibration gave this automated program a more accurate start point that is supported by qualitative analysis and subjective targets, such as water balance, that the automated computer algorithms do not consider.

5 Results and Discussion

5.1 Hydrological Results and Discussion

5.1.1 Manual Sensitivity Analysis and Model Familiarization

Several important deductions were made during the qualitative familiarization step in the SWAT model development. Kerr Brook is a flashy watershed; high flows from runoff events are significantly larger than low baseflow conditions. Land cover conditions are also characterised with low reference CNs. Due to these characteristics, initial groundwater parameters had significant influence on flow rates. This sensitivity highlighted the importance of having an objective approach to estimate surface-groundwater flow ratios. A two-parameter digital baseflow filter was integrated into the manual calibration procedure because of this. This enabled a more objective approach to account for surface runoff and groundwater flow contributions.

The groundwater reservoir framework in SWAT had limited ability to accurately predict extended baseflow conditions. The flashy nature of the hydrograph required rapid baseflow contributions, leaving no component for a slow baseflow recession to maintain extended flow conditions. There is only one groundwater reservoir in SWAT so this aquifer rapidly drained. This was not a large concern because event-based water quantity and quality was of prime interest for this study and baseflow would be unlikely to contribute sediments. Extended baseflow contributions were also generally small compared to event responses. An alternative baseflow filter approach was adopted during manual calibration because of this issue. This involved subtracting baseflow contributions from a conceptual hard rock aquifer from the observed data and then using these adjusted observations as a calibration target. Water balance was maintained by accounting for this loss in the deep aquifer recharge component in SWAT, which is considered as a loss to the system in this model. This process is further discussed in Sections 3.6 and 5.1.3.

Difficulties were confronted when simulating vegetation conditions, primarily affecting ET processes. SWAT has issues simulating mature tree stands (Gautam, 2012) because plant growth sub-models were primarily designed for agricultural crops. Plant growth and biomass parameters proved to be problematic in this model. This primarily concerned difficulties in achieving reasonable LAI results. There is also limited data concerning vegetation conditions in the study area. For these reasons plant parameters were adjusted to provide a constant LAI to maintain constant canopy interception and ET effects. Further consideration of plant parameters and growth conditions were outside the scope of this study; however, remain to be an area for improvement.

Occasionally, peak runoff events were simulated one day in advance of that observed. Adjusting routing parameters did little to alleviate this issue. This was expected to be largely due to the daily time-step used in this model. Many of these premature events received rain late in the day and the ability to transform this rain into runoff for the next day was limited by this daily time-step. The flashy nature of this watershed was also expected to exacerbate this issue. Hourly rainfall data can be used in SWAT and was used during the development of this model. However, issue were confronted with routing errors at an hourly time-step, which were suspected to be from errors in the model’s code. SWAT was not developed for high resolution temporal scales and most users evaluate results at the monthly or annual time-scale. Daily hydrological conditions were considered in this report because daily statistics were observed to be relatively strong and provided more insight into watershed conditions and simulation capabilities than monthly or annual reporting. Monthly and annual sediment yields were considered because there are limited references advocating support for daily reporting of sediment yield simulations with USLE derivatives.

5.1.2 Initial Automated Sensitivity Analysis and Calibration

This step provided insight into parameter sensitivity; however, it did little to enhance model parameters. The manner in which this exercise was conducted may have limited its value since a significant number of parameters were included in this analysis over substantial parameter ranges.

Parameter sensitivities are numbered in priority order in Appendix F based on α and *t-stat* ranking. Highly sensitive parameters were generally consistent between different automated iterations; however, this consistency was reduced for less sensitive parameters. In summary, the depth to impermeable layer parameter (DEP_IMP) was the most sensitive input variable. This parameter controls subsoil percolation rate which directly affects groundwater flow, soil moisture and SCS CNs with a soil moisture adjustment factor. A SCS CN adjustment factor (CNCOEF), considering antecedent climate conditions, was among the most sensitive parameters. Groundwater delay (GW_DELAY) and a surface runoff lag parameter (SURLAG) were also generally sensitive. The flashy nature of the hydrograph supports the assumption that these two parameters were not highly influential in event hydrology, so they were generally not considered in further calibration efforts. Oddly, the sensitivity of SCS CNs, categorized into their LULC classes, were highly variable and generally not very significant. However, this is consistent with a previous study in New Brunswick where SCS CN adjustments did not significantly affect flows (Yang, 1997). Also, the rapid groundwater contributions in this watershed would also reduce the sensitivity of CNs. In the GLUE analysis SCS CNs ranked from 7^{th} to being insignificant ($\alpha > 0.1$). Disaggregating the SCS CNs into their LULC classes may also be attributable to its relative insensitivity.

Many parameter dot plots did not converge to a specific range. Dot plots were constructed for each parameter included in the analysis; the parameter adjustment (x-axis) and resultant objective function value (y-axis) are displayed in these plots. Two example dot plots are displayed in Figure 11, where the CN is seen to converge to zero, indicating that no adjustment is necessary, and the groundwater recession constant (ALPHA_BF) does not converge, indicating many adjustments were capable of achieving strong statistical criteria. A dot plot is observed to converge when there is a significant improvement in the objective function within a certain adjustment range. Many of these plots did not converge, indicating no specific adjustments were capable of achieving significantly improved results. These plots also indicated that many parameter adjustments were capable of achieving reasonable results and provided insight into parameter uncertainty and prediction equifinality, where many parameter sets are capable of matching observed results.

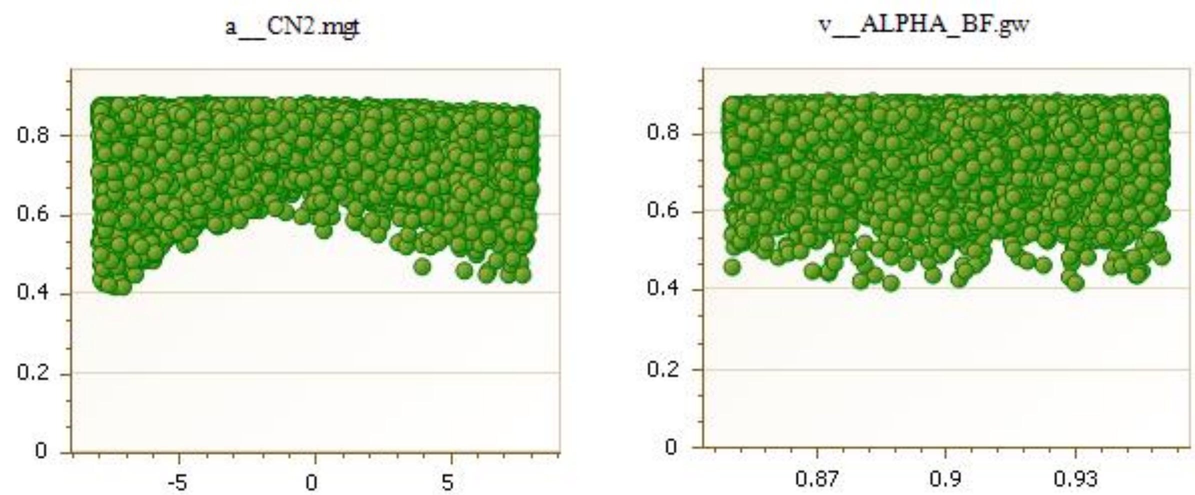


Figure 11. Converging parameter (left) and non-converging parameter (right) dot plots.

Calibration results displayed a tendency to over predict post-event baseflow recession and extended baseflow conditions. Observed baseflow and recession characteristics were generally at the minimum range of the 95PPU. Peak flows were both under and over predicted. Automated GLUE analysis 95PPU results, for 2010 and 2011, only considering the observed downstream discharge are included in Figure 12. In this figure the upper and lower 95PPU limits for simulations meeting the objective function criteria are displayed by a 95PPU band, along with the observed values. Observed values occasionally fall outside the 95PPU band. This occurs once during a high flow event which may be an indication of poor rainfall data or poor conceptualization of water storage features. Late fall observations occasionally falling outside the 95PPU band may be attributable to snowfall and poorly simulated winter hydrology processes.

Small runoff events, throughout the spring and summer, outside the 95PPU band could be a function of VSA hydrology or poor rainfall data, to name a few potential causes for these errors.

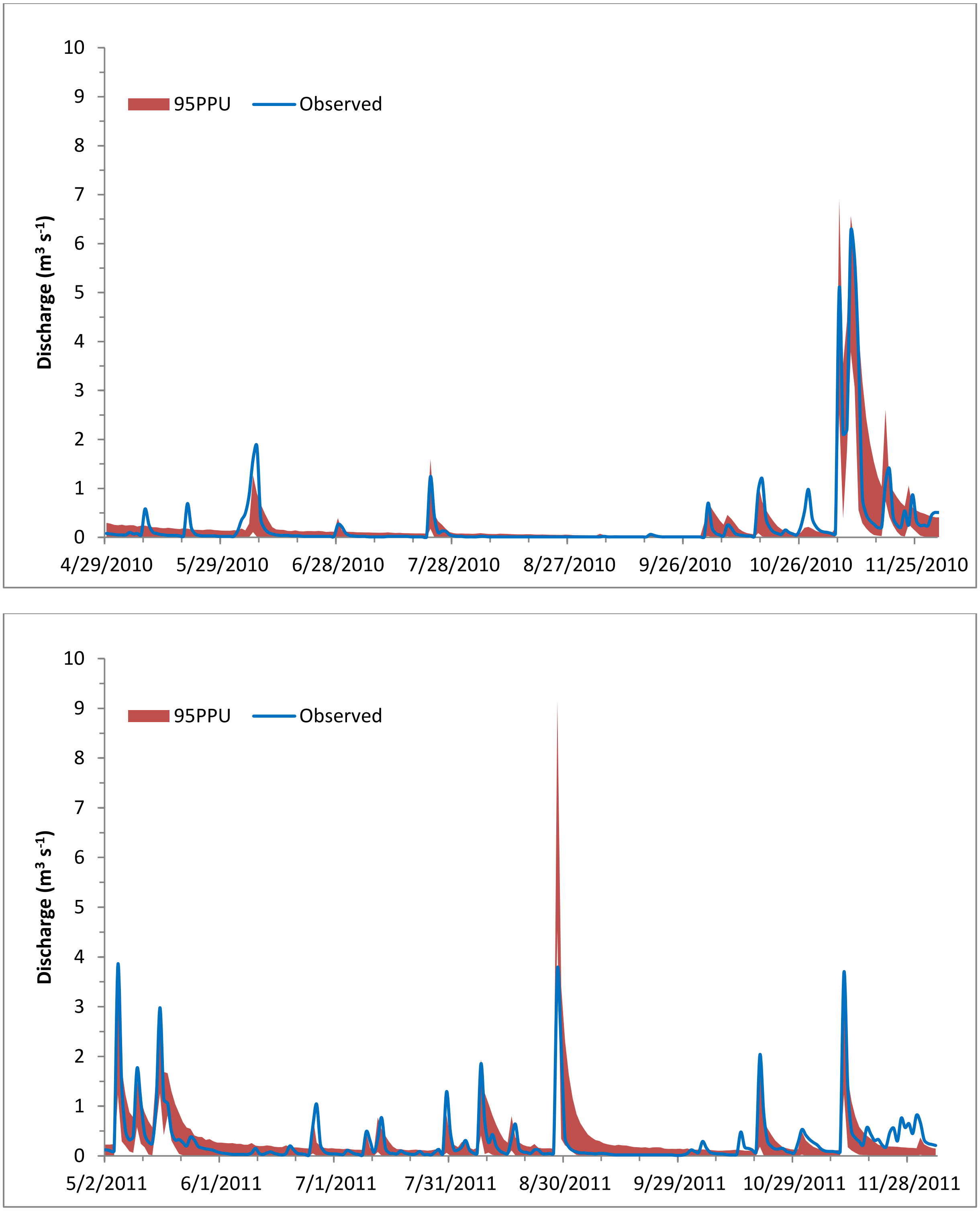


Figure 12. 95PPU plots from the downstream GLUE analysis.

5.1.3 Manual Calibration

Manual calibration demanded the most extensive effort in this analysis, resulted in the most informative deductions and yielded the best simulation results. A summary of selected simulations in this procedure are given in Appendix G, including parameter adjustments and resultant statistics. Approaches using different baseflow filter parameters also resulted in significant parameter changes. Daily downstream outflow results for the initial simulation, Sim(1), and the final simulation, Sim(r4), are displayed in Figure 13. Sim(1) was conducted using the single component baseflow filter, while Sim(r4) was conducted using the two component baseflow filter. Observed values between these two simulations are different because of this; Sim(1) displays the actual observed flow, while Sim(r4) displays the observed flow less the hard rock aquifer baseflow component.

Daily flow statistics and water balance simulations for the manually calibrated model were generally strong. Daily downstream discharge was well simulated for both years (NSE = 0.73-0.79 and R^2 = 0.86-0.88). The total simulated water yield compared well to the observed water yield (%d = -2%). Surface and groundwater components were also well balanced, compared to baseflow filter targets (%d = -11 to 10%). This criteria was satisfactory compared against literature criteria, even when summarized at the monthly time-scale (NSE > 0.5, R^2 > 0.6 and %d < 15%) (Engel et al., 2007; Jeong et al., 2010; Arnold et al. 2012). The final accepted simulation, Sim(r4), had statistics slightly weaker than other iterations. However, the baseflow separation component considered additional complexities with multiple groundwater aquifers, which better represents actual conditions. This approach was also supported from graphical baseflow separation results.

From the initial parameter set, all SCS CNs were increased. This may be attributable to poor drainage conditions created by military activity, such as cross-country vehicle manoeuvres. This may also be from soils being inaccurately classified. Soils may have slower drainage conditions due to high soil moisture conditions and shallow restricting layers. However, with the need to have a rapidly responding groundwater aquifer (GW_DELAY = 0 and ALPHA_BF = 0.99), these CN adjustments had only minor effects on the daily stream hydrograph. These adjustments were more sensitive when considering deep aquifer loss with the two component baseflow filter.

The plant water uptake coefficient (EPCO) was also reduced to increase total water yields. Annual ET predictions seemed excessively high at 650 mm yr^{-1}, compared to literature reports in the order of 440 mm yr^{-1} (Fernandes et al., 2007). Average PET for the two eco-districts this watershed borders is also in the order of 556 mm yr^{-1} (Marshall et al., 1999), compared to a PET of 777 mm yr^{-1} simulated in this model. There are two primary possibilities that may explain these discrepancy; 1) simulated PET and ET may be realistic and reflect climate change and localized land cover conditions; and 2) the model is over predicting ET rates because of poor parameterization, most likely with vegetation related parameters. While annual ET rates are observed to be increasing in Atlantic Canada (Fernandes et al., 2007), this simulated increase seems excessive. The latter possibility is more likely and calls for additional attention to plant, soil and ET parameters.

The model had difficulty simulating extended baseflow conditions, as discussed previously. Reducing percolation rates, by reducing the depth to impermeable layer (DEP_IMP), improved these results but to a limited degree. Also, only small areas of the watershed were able to accommodate this adjustment to ensure extended baseflow conditions were not over predicted. This included HRUs with level topography or HRUs underlain by Tracy Loam. Both of these adjustments may be realistic and both had significant influence on the upstream drainage basin.

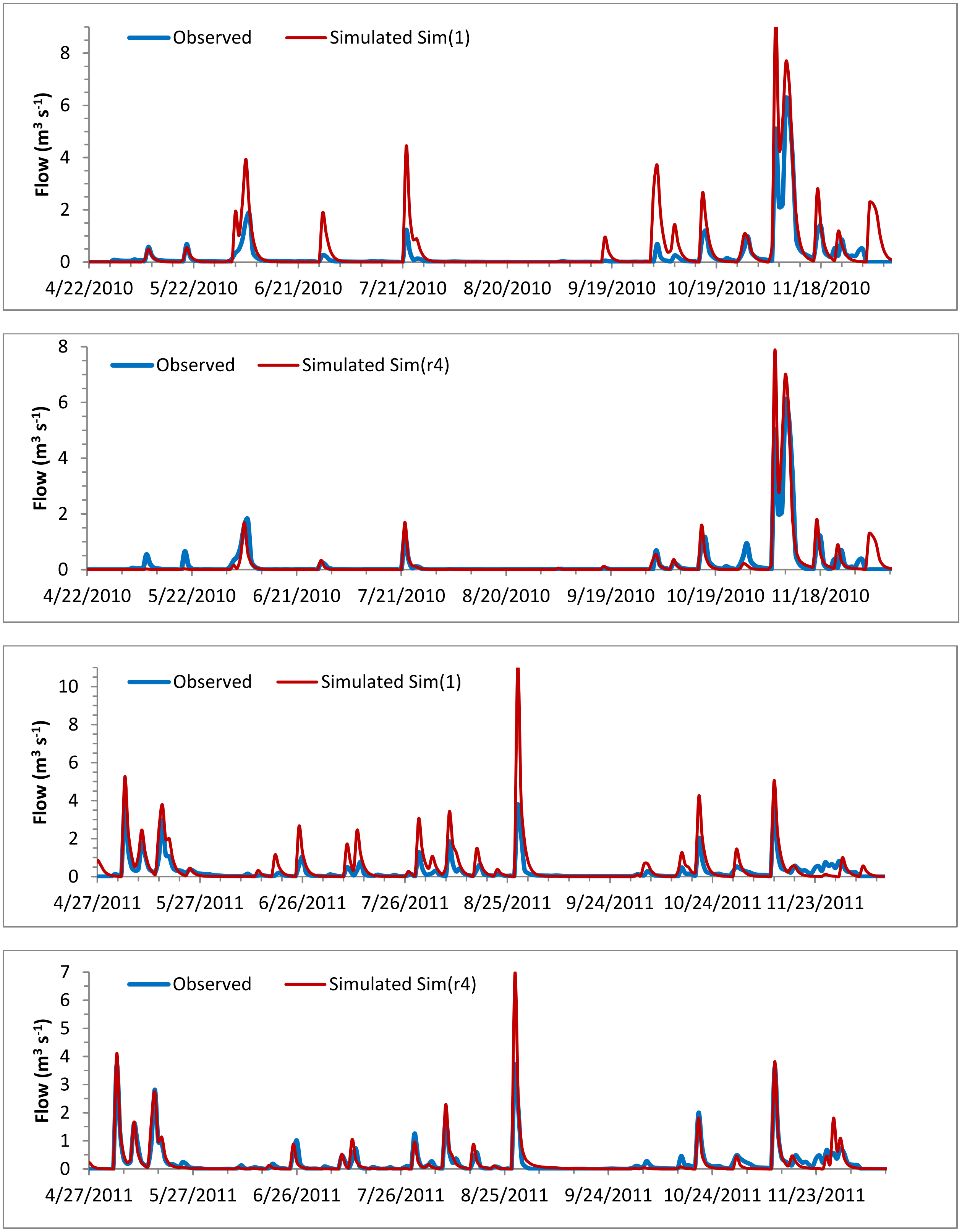


Figure 13. Observed and simulated downstream daily discharge for Sim(1) and Sim(r4).

Wetlands proved to be an effective means to reduce over simulated high flow events. They also were capable of altering total water yields. Wetland surface areas and drainage areas were estimated from Wet Area Mapping; however, no data were available concerning depth, volume or infiltration characteristics. One wetland in sub-basin three (SB3) was integrated into this model to improve water yield and peak flow statistics. These parameters are outlined in Appendix G. Another significant wetland identified by Wet Area Mapping in the upstream sub-basin (SB1) was not integrated into this model because water yields and peak flows were generally under simulated. This highlights potential error with this approach and other hydrological parameters. There is opportunity to improve parameterization and simulation of wetlands in this research approach, especially because many wetlands were observed to be impacted by beaver activities.

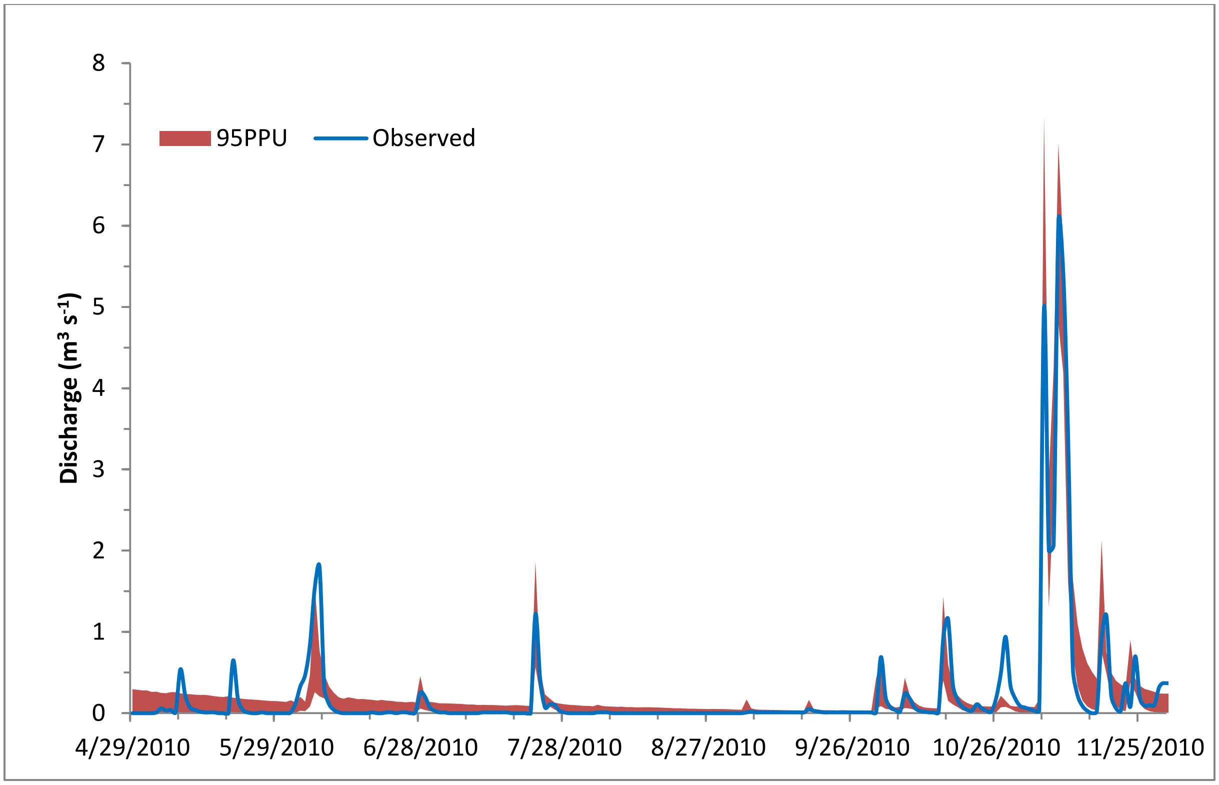
Minimizing observed rainfall data, based on adjacent meteorological stations, resulted in some peak daily discharge simulation being reduced up to 4 m^3 s^{-1}, or 60%. These adjustments significantly improved some high flow events but also degraded simulations for some medium flow events. Typically, average annual precipitation values between the three meteorological stations considered in this analysis varied within ± 1%; however, this ranged up to 10% at times. For example, in 2012, the REM02 station had an average annual precipitation 10% higher than both REM04 and REM06. Inconsistent climate record intervals between these stations limited the number of comparable periods. Additional study and consideration of climate patterns in this area have potential to significantly improve simulation results.

One limitation in this manual approach was that there was little consideration of water storage within the watershed. This limitation may be exacerbated by the fact that water balance calibration considered observation periods generally from late spring to late fall. While annual water balance storage can approach a zero net change, seasonal water storage variations may be significant. The model's hydrological elements may also poorly represent some water storage components. No extended aquifer storage was considered; aquifers typically drained completely several days after a rainfall event. Soil storage may also be poorly simulated because there was little data concerning the total soil profile depth and groundwater depth. Micro-surface depressions were also not included in this model, such as extended water storage in vehicle ruts or small depressions. While wetlands were considered in this model, wetland characteristics were subject to significant uncertainty.

5.1.4 Final Automated Calibration

Final auto-calibration conducted with GLUE improved NSE and R^2 statistics, but at the cost of deteriorating water balance statistics. The best simulation from the GLUE auto-calibration, only considering downstream discharge, achieved improved daily discharge statistics for both years (NSE = 0.82-0.91 and R^2 = 0.83-0.91); however, the total water balance deteriorated (%d = 14-17%). Also, surface and groundwater balance components deteriorated, compared to the baseflow filter targets (%d= -82 to 70%). Most parameter ranges did not significantly converge and 5,665 of the 10,000 simulations were capable of meeting the threshold criteria (NSE > 0.8). 95PPU statistics were also generally poor (P-factor = 0.51 and R-factor = 0.36). The 95PPU plot, considering only downstream flow, is displayed in Figure 14.

When considering upstream and downstream observations, GLUE was still able to improve downstream simulation results (NSE = 0.75-0.89 and R^2 = 0.78-0.89); however, 95PPU statistics were unsatisfactory (P-factor = 0.12 and R-factor = 0.09). The best simulation's total water balance was still strong (%d = -2 to 4%); however, surface and groundwater components were weak, compared to the baseflow separation targets (%d= -58 to 53%). A similar pattern was also apparent for upstream statistics, with simulations generally underestimating observed values. Results, parameter adjustments and parameter sensitivity rankings for this analysis are summarized in Appendix F.



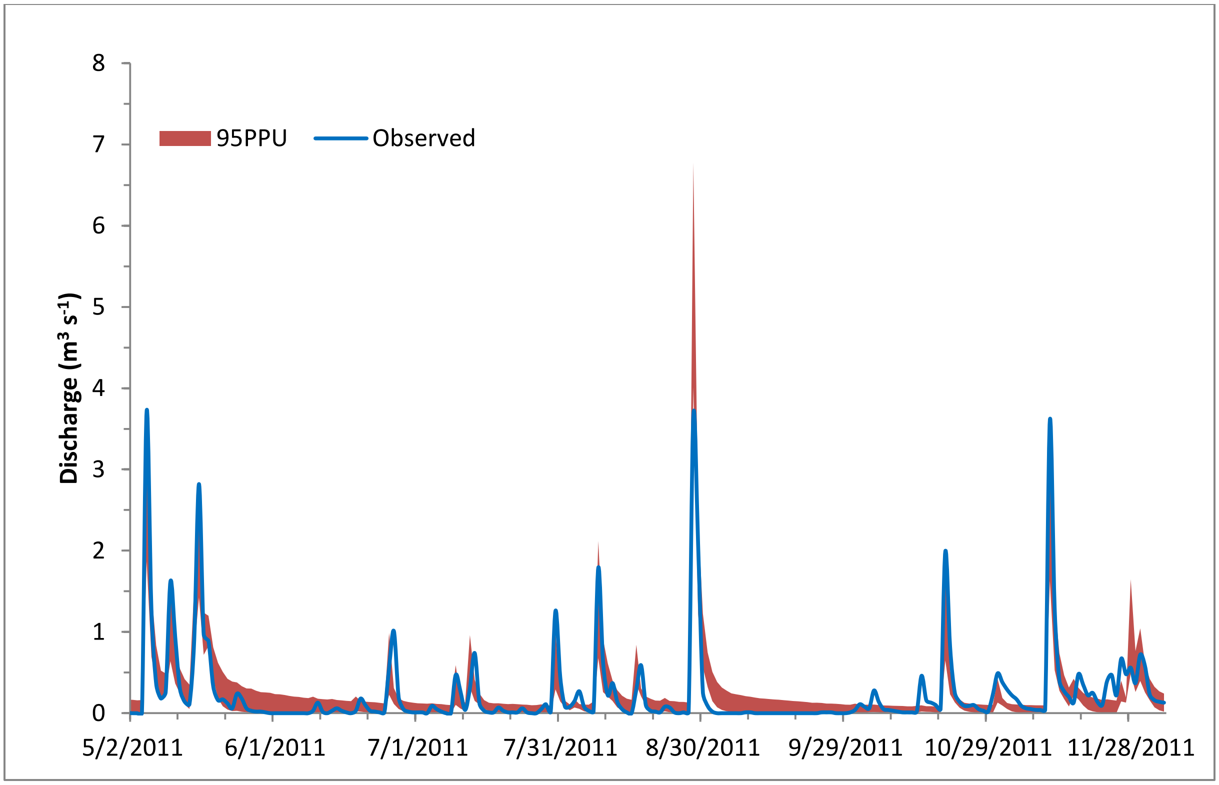


Figure 14. 95PPU plot from the final downstream GLUE analysis.

Observed discharges were still generally at the lower limit of the 95PPU band, similar to the initial GLUE analysis. SWAT also displayed a tendency to simulate elevated baseflow recession discharge, while still achieving reasonable statistics. Similar issues from the initial GLUE analysis, regarding observations falling outside the 95PPU band, were also apparent in this analysis. Again, these issues were primarily suspected to be due to poor rainfall data, conceptual water storage errors and poor winter hydrology simulations. All automated calibration approaches degraded water balance statistics, and had relatively poor P and R-values. The best simulations from these automated approaches were rejected due to these issues and the manually calibrated model was retained for validation. Many simulations were capable of achieving strong statistics and most parameter ranges did not converge to informative values. This analysis highlighted important aspects of parameter uncertainty and model equifinality, particularly if no hydrograph separation analysis is considered.

5.1.5 Validation and Final Remarks

Model simulations were more effective during the calibration time periods than the validation periods in 2009 and 2012. Validation statistics are summarized in Table 6 and daily downstream discharge is included in Figure 15. Observed and simulated downstream discharge plots are also displayed in Figure 16. There were several events in 2009 where peak flows were simulated one day in advance of observed flows. This is likely attributable to the daily time-step used in SWAT, as previously discussed. This significantly impacted NSE and R^2 statistics but had less influence on water balance statistics. In 2012 flows were consistently over simulated during the fall period. The first rainfall event of this season was the largest in the entire simulation period, with 118 mm falling at REM02 on 9/5/2012. It is suspected that this error is attributable to a disturbance that this storm event caused to the stream channel or data level logger, disrupting the stage-discharge relationship of the monitoring site. It is also possible that this error may be attributable to a conceptual error in the model, in the form of some storage component. This event was preceded by an extended dry period which may have emptied a storage component usually full during normal water years, such as wetlands, groundwater storage or surface depressions. However, it is suspected that this is unlikely considering this overestimation persisted for more than a month, which included multiple runoff events. This is further supported by the fact the upstream flow conditions were generally well simulated for 2012. The only depth-discharge measurement in 2012 at this location was conducted in August by DFO personnel.

Table 6. Downstream and upstream validation statistics.

Year	Total Yield %d	Surface Runoff %d	Groundwater %d	Deep Aquifer Recharge %d	NSE	R^2
Downstream						
2009	-2	53	-81	-89	0.47	0.5
2012	-73	-92	-43	-56	-0.46	0.64
Upstream						
2009	34	66	-17	4	0.47	0.50
2012	-12	-17	2	38	0.54	0.62

Over the entire simulation period there were zero days when downstream flows fell below 0.005 m^3 s^{-1}, 64 days when flows fell below 0.01 m^3 s^{-1}, and 150 days when flow fell below 0.02 m^3 s^{-1}. Using the single component baseflow filter and accounting for no deep aquifer recharge 83, 101 and 145 days were simulated for these daily flow intervals, respectively. This indicated that low flow conditions were generally underestimated. Observed values, less the hard rock aquifer baseflow filter component, saw 207, 300 and 351 days where these flows were observed, for the respective intervals above. This corresponded to 281, 322 and 385 days where simulated values match these flow intervals, respectively. This showed that utilizing the two component baseflow filter approach slightly improved the ability to account for low flow conditions.

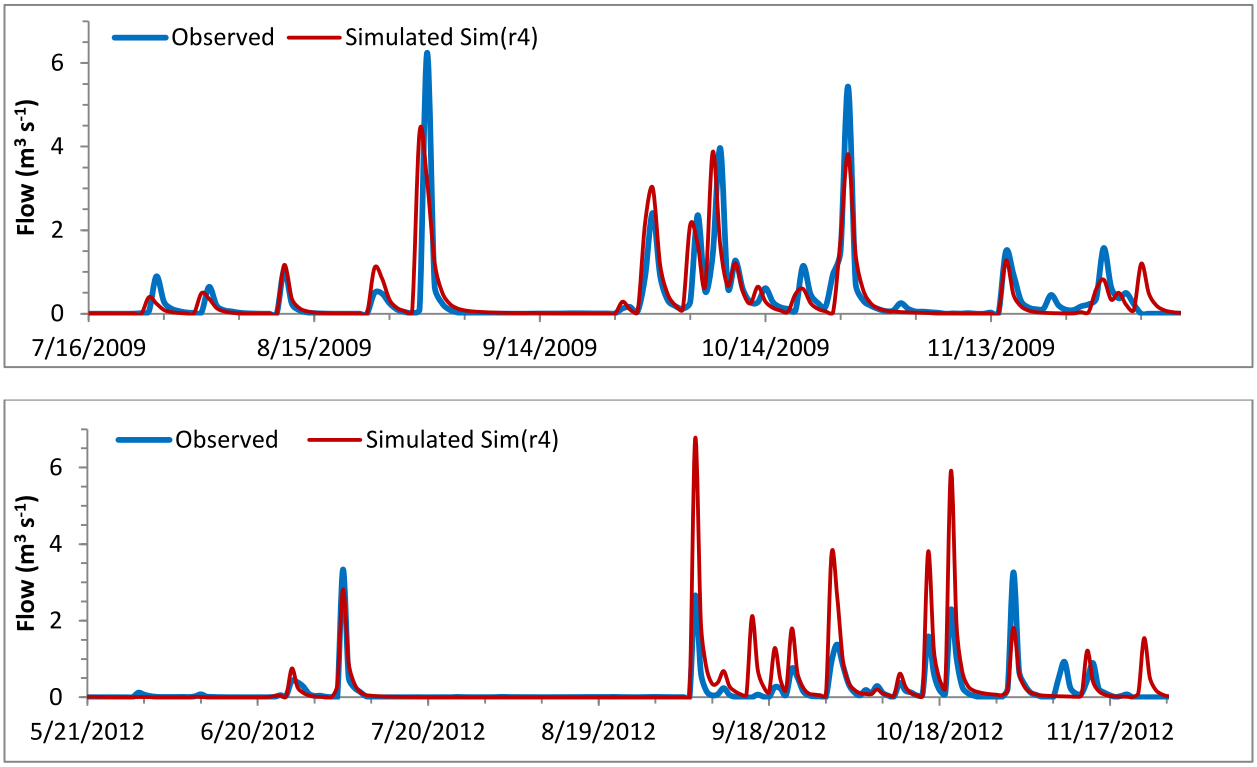


Figure 15. Downstream discharge validation period.

Upstream results for the validation periods in 2009 and 2012 varied; discharge values were both overestimated and underestimated. Mid-range flows were generally well simulated, while high flows were either over or underestimated. Total water balance for these two years ranged from 34% to -12%. Surface runoff, groundwater flow and deep aquifer recharge values ranged from 66% to -17%, 2% to -27% and 4% to 38%, respectively. Upstream simulations in 2009 achieved a NSE = 0.47 and R^2 = 0.50, while 2012 simulations achieved a NSE = 0.54 and R^2 = 0.62. The flat topography, well forested conditions, dominant Tracy Loam soil coverage and proximity to another eco-region are unique conditions of the upstream drainage basin which may account for some of these errors and provides additional opportunity for model enhancements in order to improve these results. Additional upstream results are located in Appendix H.

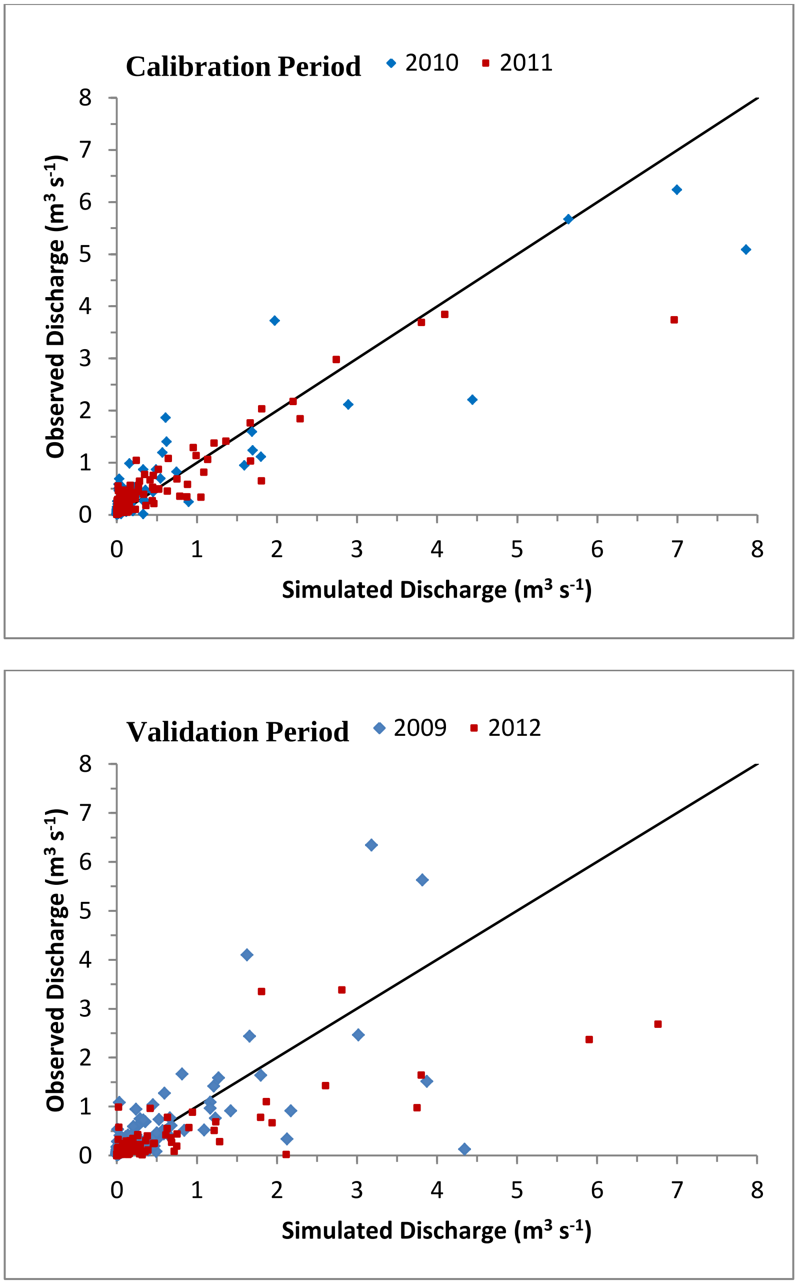


Figure 16. Observed and simulated downstream discharge plots.

5.2 Sediment Results and Discussion

Monthly sediment yields were relatively adequate with no calibration to sediment parameters, such as slope length (SLSUBBSN), cover-factors (USLE_C), and vegetated filter strip parameters. Sediment yield results from the two component baseflow separation method, compared to the TSS regression model, are summarized in Table 7. Monthly sediment yields from the TSS regression analysis and final SWAT simulation, Sim(r4), are displayed in Figure 17.

Table 7. Downstream sediment yield statistics summary.

Year	%d	NSE	R^2
2009	44	0.38	0.86
2010	6	0.91	0.97
2011	-47	0.47	0.67
2012	-217	0.88	0.64

Upstream sediment yields were consistently overestimated, compared to the regression model. Annual sediment yields for the upstream monitoring location varied between 84% and 363%. This consistent overestimation is suspected to be attributable to the flat topography of the upstream drainage basin and because most low order streams are well buffered with forest areas. The model also tended to underestimate peak flows from many runoff events, and this would also reduce erosion rates and sediment yields. Low slope HRUs may require refined slope classification categories, such as an additional slope category between 0-4.5%. The majority of this upstream drainage basin is underlain by Tracy Loam which was estimated to be more erodible that other soils in this watershed, so soil erodibility may be a source of this error. Land cover proportions for the upstream drainage area are similar to the entire watershed so land cover parameters were not suspected to be a source of this error. Wetlands may reduce sediment yields but wetlands were not included in the upstream drainage basin due to under simulated discharge conditions. Additional upstream sediment results are location in Appendix H.

Even though simulated sediment yields may be considered adequate, this does not mean that this model is accurately simulating true erosion and sedimentation patterns. There are three main components which may account for significant uncertainties related to sediment yield variables: 1) errors in the TSS regression model; 2) inaccurate model parameters affecting various processes, such as surface runoff, vegetation cover and vegetated filter strips; and 3) conceptual errors in the model that lacks the ability to account for certain erosion processes, such as gully and channel erosion.

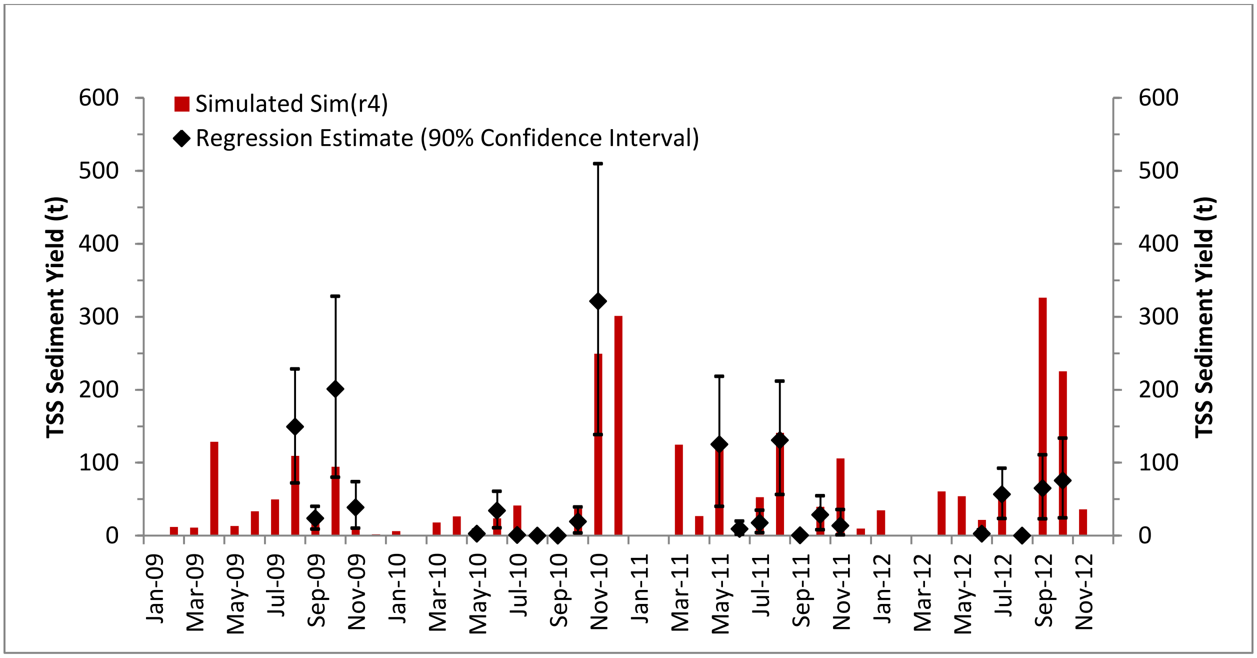


Figure 17. Downstream monthly sediment yields.

It can be seen from monthly sediment yields results, in Figure 17, that fall storms tend to dominate TSS yields. The spring freshets occasionally contributed large sediment yields but these were generally less than fall events. This is slightly suspicious because spring snowmelt events and other post-winter processes are commonly recognized to contribute to significant sediment yields (Milburn and Prowse, 1996; Yang et al., 2011). The regression model results are generally higher than the SWAT simulations. This difference may be attributable to conservative erosion related parameters, or be due to other erosion processes not simulated in this model. Also, that fact that this model did not simulate many sediment reduction features, such as vegetated filter strips, grassed waterways and surface depressions, indicate that erosion rates may be generally underestimated; however, this may correspond to underestimated sediment deposition rates as well.

6 <u>Recommendations</u>

Providing a series of recommendations was one of the objectives of this study. These recommendations are designed to target continued academic research and practical studies for military land managers. There are three different avenues for technical recommendations related to this field of study: 1) expansion of the spatial and temporal scale of this modelling exercise; 2) refinement of model parameters and observation data; and 3) enhancements to environmental modelling processes. Recommendations regarding a strategic model application approach are also discussed. These avenues are overarched by the strong recommendation that an integrated land management strategy be adopted for military lands. Stakeholders require effective and practical guidance tools to make optimal use of their real-estate assets, and resources used to manage them. Collaborative effort in selecting and achieving goals, extensive monitoring efforts and objective resource allocation are just a few crucial components of such strategies. A well designed management approach is the optimal manner to meet operational, environmental, economic and social goals under present and future conditions.

6.1 Model Expansion

There is sufficient climate and hydrometric data available to expand the SWAT model in the Gagetown RTA. There are three drainage areas within the RTA: the Nerepis River to the south; the Saint John River to the north and east; and the Oromocto River to the west. The Nerepis River has the most comprehensive data set available and the majority of manoeuvre training areas drain into this watercourse. With continued data refinement of SWAT parameters and observed data, this model could be developed for this drainage basin for an extended time period. Significant land clearance operations should be included in this model analysis to evaluate changing landscape effects. This development may enable land managers to predict hydrological and water quality impacts from future landscape alterations. This is an important time to consider this research as there are desires, and a growing requirement, to expand current manoeuvre areas.

6.2 Data Refinement

There are numerous approaches that could be applied to reduce parameter uncertainty in the SWAT model. First and foremost, sediment fingerprinting with continued flow, turbidity and event-based TSS monitoring is anticipated to be the most valuable and informative data. There is increasing interest in the use of sediment fingerprinting as a conventional watershed management tool, as discussed in Section 2.3. Findings from such a study would provide immediate and clear direction for erosion and sediment control strategies. This data would also provide valuable calibration and validation data for landscape, road and channel erosion processes. Continued monitoring of stream flow, turbidity, TSS and stream temperature would also provide data that could be used in support of additional calibration and validation efforts. Expansion of the event-based TSS monitoring data set would enable a more precise and accurate analysis of actual sediment yields. As this database expands, sufficient information would be available to support the use of daily event mean TSS concentrations, rather than utilizing regression approaches. Documentation of TSS grain size distribution, in a qualitative and quantitative manner, may also be valuable. This may provide insight into stream power conditions and stream sediment deposition and re-suspension patterns.

Baseflow separation remains to be a subjective procedure accompanied by substantial uncertainties. Hydrograph separation tracer tests, as discussed in Section 2.1, are expected to be the most effective means to objectively conduct this separation. Accurate hydrograph separation is crucial for accurate simulation of surface runoff and corresponding erosion rates. A clear understanding of these runoff characteristics, and the linkages to different land cover conditions, is important for model parameterization and alternative cover scenario evaluations.

Numerous reports in the literature utilize remote sensing techniques, supplemented with field survey data, to guide parameterization of vegetation and cover conditions. This was discussed in Section 2.5. These are important factors when concerned about distributed erosion processes. Properly characterising land cover conditions would enhance model parameterization and provide immediate guidance to target localized mitigation efforts. Bare soil surveys and remote sensing data are available for Gagetown; however, limited effort has been made to compile this information in order to objectively characterise land cover conditions. Traffic data and trafficability conditions are also available for Gagetown. An analysis should be developed considering all these factors and how they impact land cover conditions. Remote sensing approaches could also be used to objectively classify parameters, such as vegetated filter strips and slope lengths.

Rainfall data is a critical component in all hydrological models. Variability among meteorological stations in Gagetown indicate that climate patterns may be more complex than the simple meteorological station assignment used in SWAT and this study. Rainfall data could be improved upon by conducting a robust statistical analysis of available rainfall data, utilizing different rainfall distribution methods discussed in Section 2.1. This could also incorporate consideration of provincial radar data, eco-district boundaries and topographical data.

Further analysis considering different HRU definition, and cover thresholds should also be considered. Barren areas were simulated as unique land cover category in HRU analysis with a 1% cover threshold. This is excessively small compared to recommendations in the literature. It may be appropriate to lump barren areas into different land cover categories or utilize different cover thresholds for HRU definition. Validation of barren area GIS data is also recommended.

6.3 Modelling Enhancements

The following section provides a brief overview of alternative modelling approaches and SWAT enhancements. No single model is available that can accurately simulate all physical processes in a watershed. A balance must be struck between model complexity, data availability, and modelling goals. In this particular research program, SWAT was selected based on its characteristics and information provided in the literature. Nevertheless, there are additional opportunities to apply other models to this situation. This study focused on landscape hydrological, erosion and water quality processes. Only field erosion and sedimentation processes were considered with a limited distribution of land cover categories. This approach was a significant and necessary simplification of natural watershed conditions for this investigation. However, it is particularly limited in accounting for highly distributed runoff, erosion and sedimentation processes. This includes complex and dynamic channel processes that are simplified or neglected in the SWAT model. Some of these limitations could be removed or their effects decreased by enhancements to the SWAT model. Alternatively, a completely separate modelling approach may prove worthwhile.

There are several simple and conventional enhancements that could be incorporated within the SWAT model itself. First, the integration of multiple groundwater reservoirs could be conducted to enable better simulation of post-event and extended baseflow contributions. Second, VSA hydrology could be integrated into the model, as discussed in Sections 2.1 and 2.9. This may enhance hydrological predictions and identify localized areas more susceptible to runoff and erosion. Incorporation of inter-HRU interactions, such as upland and lowland sediment transport processes, could also be utilized. A refined time-scale may be valuable to consider within SWAT or another modelling program; however, as the study area increases this refined time-scale may not be necessary.

SWAT is limited in its ability to account for detailed, physically-based erosion and sediment transport processes. There are many models that can compensate for this limitation when applied to small watersheds or hillslopes. These models could be used in conjunction with SWAT to develop a multi-scale, hybrid approach to hydrological, erosion and sedimentation simulations. The USPED model is suspected to be a simple and effective tool for this type of application. Other, more complex models could also be used, such as LISEM or DHSVM. However, the enhanced complexities and resources required for the development of these physically-based models may not be effective within a practical management strategy.

Additional consideration of stream channel aggradation and degradation is highly recommended. This requires more detailed hydraulic simulations for river systems. Hydrologic disturbances within the study area may be significant and be attributable to channel instability. This instability may account for significant sediment yields and habitat degradation. Identifying quantitative relations between detailed hydrographic data and erosion processes may assist in the design of stormwater and hydraulic structures. This would also clarify the link between land management practices and river system impacts, which will enable effective selection of management approaches.

6.4 Modelling Application Strategy

Strategic watershed management approaches can take many different forms. One approach regarding modelling applications is recommended and discussed below. Such an approach could only be executed if substantial time and resources are dedicated to developing these models and instilling confidence in their results, by methods such as the recommendations previously discussed. The complexities of watershed processes and conditions at military installations would most effectively be addressed by multiple models, applied at different spatial scales, and focusing on different processes. One model application strategy for a sediment control framework is outlined in Figure 18.

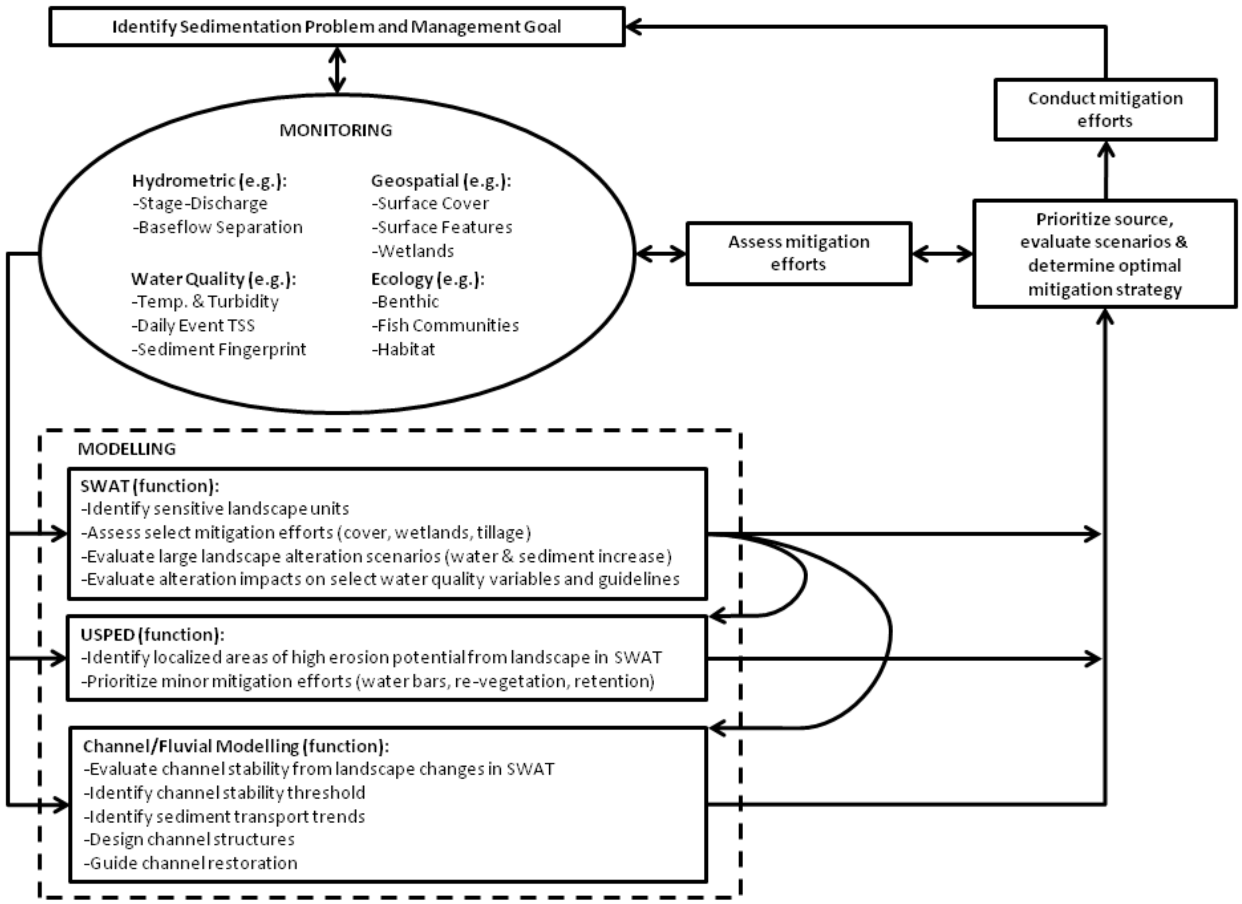


Figure 18. Model application functions and strategy.

First and foremost, problems need to be identified and clear management goals need to be selected. These problems and goals are selected considering monitoring data, environmental regulations, guidelines and eventually modelling simulations. This initial step evolves over time as information regarding these different considerations is improved upon. Monitoring data alone may provide guidance to establish management procedures and mitigation efforts; however their effectiveness can only be proven with continued monitoring and on a trial and error basis. This may lead to substantial investments of time and resources on ineffective management and mitigation practices. Alternatively, monitoring data can be used to develop, calibrate and validate environmental simulation models. When reasonable confidence is achieved in these models, then different management and mitigation strategies can be evaluated without committing resources. The optimal strategy can then be selected based on scientifically defensible logic.

Continued monitoring, and consideration of problems and goals, is still required to validate simulated management strategies; however, these strategies are more likely to be successful.

SWAT could be a key component in a model application strategy. It would primarily be used to evaluate different landscape alteration effects on watershed hydrology and sedimentation processes. Different landscape scenarios could be evaluated for their water quality guideline exceedance probabilities and the optimal scenario could be selected based on desired water quality goals. Watershed cover scenarios could also be evaluated to target water yield goals and/or desired baseflow conditions. Selected landscape mitigation practices could also be evaluated. The benefit of tillage practices on newly cleared field or large wetland construction projects could be used to estimate their impact on water quantity and quality targets. HRUs and sub-basins identified by SWAT as highly erosive landscape could be properly prioritized and targeted for mitigation efforts and/or more distributed erosion modelling simulations. This could include the application of the USPED model to guide localized sediment control measures, such as revegetation, riprap armouring, mulching and check dams. Identifying these localized erosion areas may be relatively straightforward; however, modelling the effects of sediment reduction structures would require highly distributed, physically-based models, which may not be suitable in practical management strategies at this time. Hydrological information generated in SWAT could also be used to feed distributed hydraulic models. Detailed hydraulic models could then be used to assess channel stability, primarily with respect to critical erosion thresholds, based on alternative watershed hydrological conditions.

7 Conclusions

Hydrological disturbances and erosion can have significant and detrimental impacts on terrestrial and aquatic environments. Canadian military training grounds are susceptible to such issues and should take appropriate action to mitigate these problems. This will ensure that sustainable conditions are maintained to meet operational requirements and maintain the environmental integrity of these landscapes. At this time, military land managers have limited, quantitative understanding of watershed processes and how they are affected by the diverse and unique conditions of these training areas. Practical management tools, combined with integrated management strategies, will enable these land managers to efficiently achieve these goals. Numerical watershed models, such as the Soil Water Assessment Tool, are a valuable utility that can provide practical and scientifically defensible knowledge to guide such management strategies.

The Kerr Brook SWAT model adequately simulated stream discharge during the observation periods from 2009-2011. The best simulation predicted acceptable total water yields (%d = -6 to -2%) and adequate daily flow statistics (NSE = 0.47-0.79 and R^2 = 0.50-0.88). Surface and groundwater components were also well simulated, compared to baseflow filter targets (%d = -11 to 10%). This is not to say the model confidently simulated the natural hydrological cycle. Uncertainties associated with surface runoff and baseflow ratios, soil storage, ET, wetland storage and deep aquifer loss may be significant. Many parameter combinations were capable of achieving satisfactory statistics during automated calibration approaches. Subjective baseflow filtration, along with manual calibration, proved to be the most effective means to achieve a unique and defensible solution in this application. Simulations failed to effectively predict flow conditions in the fall of 2012; however, this was suspected to be attributable to an error with the observed data during this period. Due to this error, 2012 results were neglected in the statistics reported above.

Sediment yields estimated by a regression model compared well with the SWAT model results from 2009-2011. Annual sediment yields calculated with these two models for the downstream monitoring locations achieved reasonably similar results (%d = -47 to 44%). Upstream sediment yields were not as agreeable (%d = -76 to -275), with the SWAT model consistently overestimating yields. Sediment parameters were not calibrated within the SWAT model and there was limited integration of sediment reduction structures, such as vegetated filter strips and wetlands. Simulations failed to effectively predict sediment yields for 2012; however, this was largely due to suspected errors with the observed flow data. Due to this error, 2012 results were neglected in the statistics reported above.

This research has demonstrated that SWAT is a capable and effective tool for simulating large-scale hydrological and erosion processes. There were many limitations of this model but limiting simplifications make this model a good candidate for a practical management tool. There are also many different approaches that may be capable of compensating for these current limitations. With continued research, hydrological and water quality impacts from select military activities and landscape alterations may be assessed with this model. Select management practices, such as mulching, wetland construction and tillage operations, also have the potential to be simulated in this model in order to guide land management strategies.

References

Abbaspour, K.C. (2012). Soil Water Assessment Tool Calibration and Uncertainty Programs: A User Manual. Swiss Federal Institute of Aquatic Science and Technology, EAWAG.

Abbaspour, K.C., J. Yang, I. Maximov, R. Siber, K. Bogner, J. Mieleitner, J. Zobrist and R. Srinivasan (2007). Modelling Hydrology and Water Quality in the Pre-Alpine/Alpine Thur Watershed Using SWAT. Journal of Hydrology, 333, 413-430.

Abbott M.B. and J.C. Refsgaard (1996). Distributed Hydrological Modelling. Kluwer Academic Publishers, Boston, Massachusetts.

Agriculture and Agri-Food Canada (2012). Soil Survey Reports for New Brunswick. Agriculture and Agri-Food Canada, web-site database. Available online: http://sis.agr.gc.ca/cansis/publications/surveys/nb/index.html [Updated: January 2012].

Amon-Armah, F., E.K. Yiridoe, N.H.M. Ahmad, D. Hebb, R. Jamieson, D. Burton and A. Madani (2013). Effect of Nutrient Management Planning on Crop Yield, Nitrate Leaching and Sediment Loading in Thomas Brook Watershed. Environmental Management, 52, 1177-1191.

Arnold, J.G., D.N. Moriasi, P.W. Gassman, K.C. Abbaspour, M.J. White, R. Srinivasan, C. Santhi, R.D. Harmel, A. Van Griensven, M.W. Van Liew, N. Kannan and M.K. Jha (2012). SWAT: Model Use, Calibration and Validation. Transactions of the American Society of Agriculture and Biological Engineers 55, 4, 1491-1508.

Ascough, J.C., C. Baffaut, M.A. Nearing and B.Y. Liu (1997). The WEPP Watershed Model: Hydrology and Erosion. Transactions of the American Society of Agricultural Engineers, 40, 4, 921-933.

Bedient, P.B. and W.C. Huber (1992). Hydrology and Floodplain Analysis. Addison-Wesley Publishing, Reading, Massachusetts.

Beckers, J., B. Smerdon and M. Wilson (2009). Review of Hydrologic Models for Forest Management and Climate Change Applications in British Columbia and Alberta. FORREX, Forum for Research and Extension in Natural Resources Society, Kamloops, British Columbia.

Beven, K. and A. Binley (1992). The Future of Distributed Models: Model Calibration and Uncertainty Prediction. Hydrological Processes, 6, 3, 279-298.

Bicknell, B.R., J.C. Imhoff, J.L. Kittle Jr., T.H. Jobes and A.S. Donigian (1996). Hydrological Simulations Program – Fortran (HSPF): User's Manual for Release 11. United States Environmental Protection Agency, National Exposure Research Laboratory, Athens, Georgia and United States Geological Survey, Water Resources Division, Reston, Virginia.

Birtwell, I.K. (1999). The Effects of Sediment on Fish and Their Habitat. Canadian Stock Assessment Secretariat, Research Document 99/139.

Blasone, R.S., J.A. Vrugt, H. Madsen, D. Rosbjerg, B.A. Robinson and G.A. Zyvoloski (2008). Generalized Likelihood Uncertainty Estimation Using Adaptive Markov Chain Monte Carlo Sampling. Advances in Water Resources, 31, 630-648.

Burdett, S.M. (2013). Kerr Brook Hydrological Model. Unpublished Project Report, Royal Military College of Canada, Department of Civil Engineering, , Kingston, Ontario.

Bureau of Reclamation (2006). Erosion and Sedimentation Manuel. United States Department of the Interior, Technical Service Branch, Sedimentation and River Hydraulics Group, Denver, Colorado.

Canadian Army (2012). 5th Canadian Division Support Base Gagetown: Web-Page Index. Government of Canada. Available online: http://www.army-armee.forces.gc.ca/en/5-cdsb-gagetown/index.page [Updated: Feburary 2014; accessed: March 2014].

Canadian Council of Ministers of the Environment (1996). Canadian Water Quality Guidelines for the Protection of Aquatic Life: pH. *In* Canadian Environmental Quality Guidelines, 1996. Canadian Council of Ministers of the Environment, Winnipeg, Manitoba.

Canadian Council of Ministers of the Environment (2001). CCME Water Quality Index: User's Manual. *In* Canadian Environmental Quality Guidelines, 2001. Canadian Council of Ministers of the Environment, Winnipeg, Manitoba.

Canadian Council of Ministers of the Environment (2002). Canadian Water Quality Guidelines for the Protection of Aquatic Life: Total Particulate Matter. *In* Canadian Environmental Quality Guidelines, 1999. Canadian Council of Ministers of the Environment, Winnipeg, Manitoba.

Castonguay, M.A. and P.A. Arp (2002). Physical and Chemical Properties of Soil Around Four of Eight Meteorological Stations at CFB Gagetown, New Brunswick. University of New Brunswick, Faculty of Forestry and Environmental Management, Fredericton, New Brunswick.

Church, M. (1992). Channel Morphology and Typology, 526. *In* P. Calow and Petts G.E. (eds.), The Rivers Handbook: Hydrological and Ecological Principles, v. 1. Malden, Blackwell Scientific Publications.

Clark, L.A. and T.M. Wynn (2007). Methods for Determining Streambank Critical Shear Stress and Soil Erodibility: Implications For Erosion Rate Predictions. Transactions of the American Society of Agricultural and Biological Engineering, 50, 1, 95-106.

Collins, A.L., D.E. Walling and G.J.L. Leeks (1998). Use of Composite Fingerprints to Determine the Provenance of the Contemporary Suspended Sediment Load Transported by Rivers. Earth Surface Processes and Landforms, 23, 1, 31-52.

Colpitts, M.C., S.H. Fahmy, J.E. MacDougall, T.T.M. Ng, B.G. McInnis, V.F. Zelazny **(**1995). Forest Soils of New Brunswick. Agriculture and Agri-Food Canada, Research Branch and Natural Resources Canada, Canadian Forest Service, Contribution No. 95-38.

Culp, J.M., G.A. Benoy, R.B. Brua, A.B. Sutherland and P.A. Chambers (2009). Total Suspended Sediment, Turbidity and Deposited Sediment Standards to Prevent Excessive Sediment Effects in Canadian Streams. National Agri-Environmental Standards Initiative Synthesis, Environment Canada, Gatineau, Quebec, Report No. 13.

Dalton, J.C. (ed.) (2008). Erosion Assessments: Training Load Optimization for Environmental and Economic Considerations. United States Army Corps of Engineers, Public Works Technical Bulletin 200-3-56.

De Roo, A.P.J., V.G. Jetten and C.J. Ritsema (1996). LISEM: a Physically-Based Hydrological and Soil Erosion Model Incorporated in a GIS. Application of Geographic Information Systems in Hydrology and Water Resource Management, 235, 395-403.

Deinlein R. and A. Böhm (2000). Modeling Overland Flow and Soil Erosion for a Military Training Area in Southern Germany, 163-178. *In* J. Schmidt (ed.), Soil Erosion: Application of Physically Based Models. Springer, Berlin.

Donigian, A.S., J. Imhoff, A. Mishra, P. Deliman and E. Regan (2010). A Watershed Modeling Framework for Military Installations: Assessment of the Hydrologic and Sediment Washoff Impacts of Military Management Alternatives. Proceedings of the 2^{nd} Joint Federal Interagency Conference, Las Vegas, Nevada.

Doten, C.O., L.C. Bowling, J.S. Lanini, E.P. Maurer and D.P. Lettenmaier (2006). A Spatially Distributed Model for the Dynamic Prediction of Sediment Erosion and Transport in Mountainous Forested Watersheds. Water Resources Research, 42, 4. DOI: 10.1029/2004WR003829.

Easton, Z.M., D.R. Fuka, M.T. Walter, D.M. Cowan, E.M. Schneiderman and T.S. Steenhuis (2008). Re-Conceptualizing the Soil and Water Assessment Tool Model to Predict Runoff from Variable Source Areas. Journal of Hydrology, 348, 279-291.

Eckhardt, K. (2005). How to Construct a Recursive Digital Filter for Baseflow Separation. Hydrological Processes 19, 507-515.

Elliot, W.J., R.B. Foltz and P.R. Robichaud (2009). Recent Findings Related to Measuring and Modelling Forest Road Erosion. United States Department of Agriculture, Forest Service, Rocky Mountain Research Station, Moscow, Idaho.

Engel, B., D. Storm, M. White, J. Arnold and M. Arabi (2007). A Hydrologic/Water Quality Model Application Protocol. Journal of the American Water Resources Association, 43, 5, 1223-1236.

Estrada, E., T. Laing, V. Paquin, P. Fortin and S. Rance (2012). Benthic Invertebrate Monitoring Program for CFB Gagetown: 2011 Results and Multi-year Data Analysis. Environment Science Group, Kingston, Ontario.

Fahmy, S.H., S.W.R. Hann, Y. Jiao (2010). Soils of New Brunswick: the Second Approximation. Agriculture and Agri-Food Canada, Eastern Canada Soil and Water Conservation Centre, Publication No. NBSWCC-PRC 2010-01.

Fernandes, R., V. Korolevych, and S. Wang (2007). Trends in Land Evapotranspiration Over Canada for the Period 1960-2000 Based in In-Situ Climate Observations and Land Surface Model. Journal of Hydrometeorology, 8, 1016-1030.

Frankenberger, J.R., E.S. Brooks, M.T. Walter, M.F. Walter and T.S. Steenhuis (1999). A GIS-Based Variable Source Area Hydrology Model. Hydrological Processes, 13, 805-822.

French, R.H. (2001). Hydraulics of Open Channel Flow. *In* L.W. Mays (ed.), Stormwater Collection Systems Design Handbook. McGraw-Hill, New York.

Gaffer, R.L., D.C. Flanagan, M.L. Denight and B.A. Engel (2008). Geographic Information System Erosion Assessment at a Military Training Site. Journal of Soil and Water Conservation, 63, 1, 1-10.

Gassman, P.W., M.R. Reyes, C.H. Green and J.G. Arnold (2007). The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. Transactions of the American Society of Agricultural and Biological Engineers, 50, 4, 1211-1250.

Gautam, B. (2012). Modelling Streamflow from Forested Watersheds on the Canadian Boreal Shield Using the Soil and Water Assessment Tool. Unpublished M.Sc. Thesis, University of Saskatoon, Department of Civil and Geological Engineering, Saskatoon, Saskatchewan.

GEMTEC (2008). Best Practices Assessment: Stormwater Management. GEMTEC Ltd., Final Report to New Brunswick Environment Industry Association, Fredericton, New Brunswick.

Govers, G. (2011). Misapplication and Misconception of Erosion Models, 117-134. *In* R.P.C. Morgan and M.A. Nearing (eds.), Handbook of Erosion Modelling. Blackwell Publishing Ltd., West Sussex, United Kingdom.

Grayson, R.B., I.D. Moore and T.A. McMahon (1992). Physically Based Hydrologic Modelling: Is the Concept Realistic. Water Resource Research, 28, 10, 2659-2666.

Helsel, D.R. and R.M. Hirsch (2002). Statistical Methods in Water Resources: Techniques of Water Resources Investigations, Book 4, Chapter A3. United States Geological Survey, Reston, Virginia.

Henderson, F.M. (1966). Open Channel Flow. The Macmillan Company, New York, Collier-MacMillan Canada Ltd., Toronto, Ontario.

Hood, D. (2013). Draft Surface Water Quality Monitoring: CFB Gagetown Range and Training Area 1997-2012. Department of Fisheries and Oceans Canada, Ecosystem Management, Synoptic Data Report.

Hosseini, M., M.S.M. Amin, A.M. Ghafouri and M.R. Tabatabaei (2011). Application of Soil and Water Assessment Tools Model for Runoff Estimation. American Journal of Applied Sciences, 8, 5, 486-494.

Jager, H.I., M.S. Bevelhimer, R.L. King and K.A. Smith (2011). Landscape Influences on Headwater Streams on Fort Stewart, Georgia, USA. Environmental Management, 48, 795-807.

Jeong, J., N. Kannan, J. Arnold, R. Glick, L. Gosselink and R. Srinivasan (2010). Development and Integration of Sub-Hourly Rainfall-Runoff Modeling Capability Within a Watershed Model. Water Resource Management, 24, 4505-4527.

Jetten, V.G. and M.P. Maneta (2011). Calibration of Erosion Models, 33-51. *In* R.P.C. Morgan and M.A. Nearing (eds.), Handobok of Erosion Modelling. Blackwell Publishing Ltd., West Sussex, United Kingdom.

Kilgour, B.W., A.P. Francis and V. Mercier (2013). Reducing the Sensitivity of the Water Quality Index to Episodic Events. Water Quality Research Journal of Canada, 48, 1, 1-13.

Kitzmiller, D., D. Miller, R. Fulton and F. Ding (2013). Radar and Multisensor Precipitation Estimation Techniques in National Weather Service Hydrologic Operations. Journal of Hydrological Engineering, 18, 2, 133-142.

Klaus, J. and J.J. McDonnell (2013). Hydrograph Separation Using Stable Isotopes: Review and Evaluation. Journal of Hydrology, 505, 47-64.

Koch, D.J., P.D. Ayers, H.R. Howard and G. Siebert (2012). Vehicle Dynamics Monitoring and Tracking System. United States Army Corps of Engineers, Construction Engineering Research Laboratory, Report TR-12-11.

Kodoatie, R. (2000). Sediment Transport Relations in Alluvial Channels. PhD Thesis, Colorado State University, Department of Civil Engineering, Fort Collins, Colorado.

Koua, T.J.J., J.P. Jourda, K.J. Kouame and K.A. Anoh (2013). Assessment of Sediment and Pollutants in Buyo Lake, Ivory Coast, Using SWAT. Journal of Chemistry and Chemical Engineering, 7, 1054-1059.

Lavigne, M.P., A.N. Rousseau, R. Turcotte, A.M. Laroche, J.P. Fortin and J.P. Villeneuve (2004). Validation and Use of a Distributed Hydrological Modeling System to Predict Short Term Effects of Clear Cutting on the Hydrological Regime. Earth Interactions, 8, 1, 1-19.

Liu, S., J. Liu, S. Zhao and L.L. Tieszen (2007). Estimating Soil Erosion at Forn Benning Using the USPED Model and Consecutive Remotely Sensed Land Cover Observations. Strategic Environmental Research and Development Program, Project SI-1642.

Lord, M.L., D. Germanoski and N.E. Allmendinger (2009). Fluvial Geomorphology: Monitoring Stream Systems in Response to a Changing Environment, 69-103. *In* R. Young and L. Norby, Geological Montioring. Geological Society of America, Boulder, Colorado.

Marshall, I.B., P.H. Schut and M. Ballard (1999). National Ecological Framework. Agriculture and Agri-Food Canada, Research Branch, Centre for Land and Biological Resources Research and Environment Canada, State of the Environment Directorate, Ecozone Analysis Branch, Ottawa/Hull, Ontario. Available online: http://sis.agr.gc.ca/cansis/nsdb/ecostrat/1999report/index.html [Updated: May 2013; accessed: May 2013].

Merritt, W.S., R.A. Letcher and A.J. Jakeman (2003). A Review of Erosion and Sediment Transport Models. Environmental Modeling and Software, 18, 761-799.

Milburn D. and T.D. Prowse (1996). The Effect of River-Ice Break-Up on Suspended Sediment and Select Trace-Element Fluxes. Nordic Hydrology, 27, 69-84.

Minella, J.P.G., D.E. Walling and G.H. Merten (2008). Combining Sediment Source Tracing Techniques with Traditional Monitoring to Assess the Impact of Improved Land Management on Catchment Sediment Yields. Journal of Hydrology, 348, 546-563.

Mitasova, H. and L. Mitas (2001). Multiscale Soil Erosion Simulations for Land Use Management, 321-347. *In* R. Harmon and W. Doe III (eds.), Landscape Erosion and Evolution Modelling. Kluwer Academic/Plenum Publishers, New York.

Molinas, A. and B. Wu (2001). Transport of Sediment in Large Sand-Bed Rivers. Journal of Hydraulic research, 39, 135-146.

Morgan, R.P.C. (2011). Model Development: A User's Perspective, 9-32. *In* R.P.C. Morgan and M.A. Nearing (eds.), Handobok of Erosion Modelling. Blackwell Publishing Ltd., West Sussex, United Kingdom.

Mukundan, R., D.E. Walling, A.C. Gellis, M.C. Slattery and D.E. Radcliffe (2012). Sediment Source Fingerprinting: Transforming from a Research Tool to a Management Tool. Journal of the American Water Resources Association, 48, 6, 1241-1257.

National Council for Air and Stream Improvements (1999). Scale Considerationd and the Detectability of Sedimentary Cumulative Watershed Effects. National Council of the Paper Industry for Air and Stream Improvements, Technical Bulletin No. 776.

National Research Council (1992). Restoration of Aquatic Ecosystems. National Academy Press, Washington, DC.

Nearing, M.A., G.R. Foster, L.J. Lane and S.C. Finckner (1989). A Process-Based Soil Erosion Model for USDA-Water Erosion Prediction Project Technology. Transactions of the American Society of Agricultural Engineering, 32, 5, 1587-1593.

Nearing, M.A. and P.B. Hairsine (2011). The Future of Soil Erosion Modelling, 389-397. *In* R.P.C. Morgan and M.A. Nearing (eds.), Handobok of Erosion Modelling. Blackwell Publishing Ltd., West Sussex, United Kingdom.

Neitsch, S.L., J.G. Arnold, J.R. Kiniry and J.R. Williams (2011). Soil Water Assessment Tool Theoretical Documentation: Version 2009 TR-406. Texas Water Resources Institute and Texas A&M University System, College Station, Texas.

Newcombe, C.P. (1997). Channel Suspended Sediment and Fisheries: A Concise Guide to Impacts. Ministry of Environment, Resource Stewardship Branch, Victoria, Britich Columbia.

Ontario Ministry of the Environment (2003). Stormwater Management Planning and Design Manual. Ontario Ministry of the Environment, Queens Printing for Ontario.

Osterkamp, W.R., P. Heilman and L.J. Lane (1998). Economic Consideration of a Continental Sediment-Monitoring Program. International Journal of Sediment Research, 13, 4, 12-24.

Overton, D.E. (1966). Muskingum Flood Routing of Upland Streams. Journal of Hydrology, 4, 185-200.

Pike, R.G., T.E. Redding, R.D. Morre, R.D. Winkler and K.D. Blandon (eds.) (2010). Compendium of Forest Hydrology and Geomorphology in British Columbia. B.C. Ministry of Forest and Range, Forest Science Program, Victoria, British Columbia and Forum for Research and Extension in Natural Resources, Kamloops. British Columbia Land Management Handbook, 66.

Raleigh, R.F. (1982). Habitat Suitability Index Models: Brook Trout. United States Department of the Interior, Fish and Wildlife Service, Fort Collins, Colorado, FWS/OBS-82/10.24.

Rasmussen, P.P., J.R. Gray, G.D. Glysson and A.C. Ziegler (2011). Guidelines and Procedures for Computing Time-Series Suspended-Sediment Conventrations and Loads from In-Stream Turbidity-

Sensor and Streamflow Data: United States Geological Survey Techniques and Methods, Book 3, Chaper C4. United States Geological Survey, Reston, Virginia.

Remus, J.I. and M. Jonas (2010). River Engineering: Past, Present and Future – A Comprehensive Systems Approach. United States Army Research, paper 216.

Rosgen, D.L. (1996). Applied River Morphology. Wildland Hydrology Books, Padosa Springs, Colorado.

Schmidt, J. (1991). A Mathematical Model to Simulate Rainfall Erosion. *In* H.R. Bork, J. De Ploey and A.P. Schick (eds.), Erosion, Transport and Deposition Processes – Theories and Models. Catena, Supplement 19, 101-109.

Sharpley, A.N., and J.R. Williams (eds.) (1990). EPIC-Erosion Productivity Impact Calculator, 1. Model Documentation. United States Department of Agriculture, Agricultural Research Service, Technical Bulletin 1768.

Singh, V.P. (1995). Computer Models of Watershed Hydrology. Water Resources Publications, Highland Ranch, Colorado.

Smedley, R.A. (2009). Fish Condition and Community Structure in an Agricultural Landscape. Unpublished M.Sc. Thesis. University of New Brunswick, Department of Biology, Fredericton, New Brunswick.

Smith, A. (2014). Strategies for the Management of Fisheries and Aquatic Habitat at 5th Canadian Division Support Base Gagetown: draft. 5th Canadian Division Support Group, Environmental Service Branch, Oromocto, New Brunswick.

Staley, N.A., T. Wynn, B. Benham and G. Yagow (2006). Modeling Channel Erosion at the Watershed Scale: Model Review and Case Study. Center for TMDL and Watershed Studies, Biological Systems Engineering, Virginia Tech, Document No. 2006-0009.

Stanley, B. and P. Arp (2002). Effects of Forest Harvesting Basin-Wide Water Yield in Relation of % of Watershed Cut: A Review of Literature. University of New Brunswick, Faculty of Forestry and Environmental Management, Fredericton, New Brunswick.

Steichen, J.M., S.L. Hutchinson, N. Zhang, J.M.S. Hutchinson, C.J. Oviatt, A. Anderson, T. Keane and P.L. Barnes (2008). Assessing the Impact of Maneuver Training on NPS Pollution and Water Quality. Strategic Environmental Research and Development Program, Project SI-1339.

Tamene, L. and P.L.G. Vlek (2008). Soil Erosion Studies in Northern Ethiopia, 73-100. *In* A.K. Braimoh and P.L.G. Vlek (eds.), Land Use and Soil Resources. Springer Science and Business, Dordrecht, Netherlands.

Todini, E. (2007). Hydrological Catchment Modelling: Past, Present and Future. Hydrology and Earth System Science, 11, 1, 468-482.

Toronto and Region Conservation Authority (2010). Low Impact Development Stormwater Management and Planning Design Guide. Toronto and Region Conservation Authority. Available online: http://sustainabletechnologies.ca/wp/clean-water/stormwater-management/water-balance-approach/low-impact-development-stormwater-management-planning-and-design-guide/ [Accessed: March 2014].

Tuppand, P., K.R. Douglas-Mankin, T. Lee, R. Srinivasan and J.G. Arnold (2011). Soil Water Assessment Tool Hydrological/Water Quality Model: Extended Capability and Wider Adoption. Transactions of the American Society of Agricultural and Biological Engineering, 54, 5, 1677-1684.

United States Environmental Protection Agency (2000). Estimating Hydrology and Hydraulic Parameters for HSPF. United States Environmental Protection Agency, Office of Water, Basins Technical Note No. 6.

United States Environmental Protection Agency (2006). Sediment Parameter and Calibration Guidance for HSPF. United States Environmental Protection Agency, Office of Water, Technical Note 8.

United States Environmental Protection Agency (2013). National Summary of Impaired Waters and TMDL Information. United States Environmental Protection Agency. Available online: http://iaspub.epa.gov/waters10/attains_nation_cy.control?p_ report_ type=T#causes_303d [Updated: March 2014; accessed: March 2014].

Vanoni, V.A. (ed.) (2006). Sedimentation Engineering. Manuals and Reports on Engineering Practice, American Society of Civil Engineering, No. 54. Reston, Virginia.

Vega-Nieva, D.J., P.N.C. Murphy, M. Castonguay, J. Ogilvie and P. Arp (2008). A Modular Terrain Model for Daily Variations in Machine-Specific Forest Soil Trafficability. Canadian Journal of Soil Science, 89, 1, 93-109.

Wall, G.J., D.R. Coote, E.A. Pringle and I.J. Shelton (2002). Revised Universal Soil Loss Equation for Application in Canada: A Handbook for Estimating Soil Loss from Water Erosion in Canada. Agriculture and Agri-Food Canada, Research Branch, Ottawa, Contribution No. AAFC/AAC2244E.

Warren, S.D. (1998) Digital Terrain Modelling and Distributed Soil Erosion Simulations/Measurement for Minimzing Environmental Impact of Military Training. US Army Corps of Engineers, Construction Engineering Research Laboratories, Champaign, Illonois, Report No. IR 99/12.

Warren, S.D., V.E. Diersing, P.J. Thompson and W.D. Goran (1989). An Erosion-Based Land Classification Systems for Military Installations. Environmental Management, 13, 2, 251-257.

Warren, S.D., H. Mitasova, M.G. Hohmann, S. Landsberger, F.Y. Iskander, T.S. Ruzycki and G.M. Senseman (2005). Validation of a 3-D Enhancement of the Universal Soil Loss Equation for Prediction of Soil Erosion and Sediment Deposition. Catena, 64, 281-296.

Watson, B.M., R.A. McKeown, G. Putz and J.D. MacDonald (2008). Modification of SWAT for Modelling Streamflow from Forested Watersheds on the Canadian Boreal Plain. Journal of Environmental Engineering Science, 7, 145-159.

Wicklund, R.E. and K.K. Landmaid (1953). Soil Survey of Southwestern New Brunswick. Canada Department of Agriculture, Experimental Farms Service, Fredericton, New Brunswick.

Wigmosta, M.S., L.W. Vail and D.P. Lettenmaier (1994). A Distributed Hydrology-Vegetation Model for Complex Terrain. Water Resource Research, 30, 6, 1665-1679.

Wigmosta, M.S., L. Lane, A. Coleman, J. Tagestad and D. Roberts (2007). Development of an Adaptive Framework for Management of Military Operations in Arid/Semi-Arid Regions to Minimize Watershed and In-stream Impacts for Non-Point Pollution. Strategic Environmental Research and Development Program, Project SI-1340.

Williams, J.R. (1969). Flood Routing with Variable Travel Time or Variable Storage Coefficients. Transactions of the American Society of Agricultural Engineers, 12, 1, 100-103.

Williams, J.R. (1980). SPNM, A Model for Predicting Sediment, Phosphorus and Nitrogen Yields From Agricultural Basins. Water Resource Bulletin, 16, 843-848.

Winchell, M., R. Srinivasan, M. Di Luzio and J. Arnold (2007). ArcSWAT Interface for SWAT2005: User's Guide. Blackland Research Center, Texas Agricultural Experiment Station, Temple, Texas and Grassland, Soil and Water Research Service, United States Department of Agriculture Research Service, Temple, Texas.

Wischmeier, W.H. and D.D. Smith (1965). Predicting Rainfall-Erosion Losses from Cropland East of the Rocky Mountains – Guide for Selection of Practices for Soil and Water Conservation. United States Department of Agriculture, Agriculture Handbook No. 282.

Wong, I.W., W.G. Booty, G. Benoy, C. Nielsen, P. Fong and R.C. McCrimmon (2009). Integrated Land and Water Scenarios of the Raisin River Watershed Using the SWAT Model. Water Quality Research Journal of Canada, 44, 4, 379-391.

Yang, J., P. Reichert, K.C. Abbaspour, J. Xia and H. Yang (2008). Comparing Uncertainty Analysis Techniques for a SWAT Application to the Chaohe Basin China. Journal of Hydrology, 358, 1-23.

Yang, Q., G.A. Benoy, Z. Zhao, T.L. Chow, C.P.A. Bourque and F.R. Meng (2011). Watershed-Level Analysis of Exceedance Frequencies for Different Management Strategies. Water Quality Research Journal of Canada, 46, 1, 64-73.

Yang, Q., G.A. Benoy, T.L. Chow, J.L. Daigle, C.P. Bourque and F.R. Meng (2012). Using the Soil and Water Assessment Tool to Estimate Achievable Water Quality Targets Through Implementation of Benificial Management Practices in Agricultural Watersheds. Journal of Environmental Quality, 41, 1, 64-72.

Yang, W., X. Wang, S. Gabor, L. Boychuk and P. Badiou (2008). Water Quality and Quality Benefits from Wetland Conservation and Restoration in the Broughton's Creek Watershed. University of Guelph, Department of Geography, Guelph, Ontario, Tarleton State University, Department of Engineering and Physics, Stephenville, Texas and Ducks Unlimited Canada.

Yang, C.T. (1996). Sediment Transport Theory and Practice. The McGraw-Hill Companies, Inc., NewYork.

Yang, Y. (1997). Evaluating Agricultural Non-Point Source Pollution Using the Soil and Water Assessment Tool. Unpublished B.Sc. Thesis, University of New Brunswick, Department of Civil Engineering, Fredericton, New Brunswick.

Appendix A Initial Watershed Parameters

General Watershed Parameters:

Process	Parameter	Description	Value	Total Range	Remarks/References Default reference (Neitsch et al., 2011)
Surface Runoff	CN2	SCS CN (average moisture, HYDGRP)	A, B, C, D	0-99	
	FRST	*Mixed Forest (Good)*	30, 55, 70, 77	30-83	Undisturbed
	RNGE	*Grasslands (Poor)*	68, 79, 86, 89	30-89	Vehicle disturbance
	RNGB	*Brush lands*	35, 56, 70, 77	30-89	Occasional vehicle disturbance
	BARR	*Barren lands, roads & tracks*	74, 84, 88, 90	72-94	Average gravel/dirt roads/fallow
	HYDGRP	Soil Hydrologic Group	-	A-D	Various soil surveys
	TRCL	*Tracy Loam*	C	B-C	
	PGSL	*Parleeville Gravelly Sandy Loam*	B	A-B	
	CNCOEF	Weighting Retention Coefficient	1	0.5-2.0	Default for ET method
	CNOP	Operation CN adjustment	-	-	No operations simulated
	CH_N(1)	Tributary Channel Manning's n	0.04	0.025-0.15	Clean, winding, pools, shoals (French, 2001)
	SURLAG	Runoff lag Coefficient	4	1-24	Flashy hydrograph
	CH_K(1)	Transmission losses (mm/hr)	0	0-300	Wet area with non-zero baseflow
Evapotranspiration	Can_{mx}	Maximum Canopy Storage (mm)	0	-	(USEPA, 2000)
	FRST	*Mixed Forest*	4	0-5	
	RNGE	*Grasslands*	1	0-5	
	RNGB	*Brush lands*	2	0-5	
	BARR	*Barren lands, roads & tracks*	0	0	
	EPCO	Plant Uptake Compensation Factor	1	0.01-1	(USEPA, 2000)
	FRST	*Mixed Forest*	0.8	0.6-0.8	
	RNGE	*Grasslands*	0.6	0.4-0.6	
	RNGB	*Brush lands*	0.7	0.6-0.8	
	BARR	*Barren lands, roads & tracks*	0.4	0.1-0.4	
	ESCO	Soil Evaporation Coefficient	0.95	0.01-1	Default

Groundwater	GW_DELAY	Aquifer Recharge Delay Time (days)	0.25	0-10	Flashy hydrograph, low baseflow
	GWQMN	Baseflow Water Level Threshold (mm)	0	0-5000	
	ALPHA_BF	Baseflow Recession Constant	0.9	0-1	Flashy hydrograph, low baseflow
	REVAPMN	Aquifer Revaporization Threshold (mm)	0	0-500	
	GW_REVAP	Revaporization Coefficient	0.02	0.02-0.2	Default
	RCHRG_DP	Deep Aquifer Percolation Coefficient	0.05	0-1	Default
Erosion	USLE_K	Soil Erodibility (0.013 metric ton $m^2/(m^3$-metric ton cm))	-	-	
	TRCL	*Tracy Loam*	0.13	0.12-0.36	See soil parameters
	PGSL	*Parleeville Gravelly Sandy Loam*	0.11	0.09-0.28	See soil parameters
	USLE_C	Minimum Cover Factor	-	-	Various (variable) reports
	FRST	*Mixed Forest*	0.001	0.0-0.02	
	RNGE	*Grasslands*	0.1	0-0.45	
	RNGB	*Brush lands*	0.05	0-0.4	
	BARR	*Barren lands, roads & tracks*	0.5	0.2-0.5	Mixed road classes and barren areas
	USLE_P	Support Practice Factor	1	1	No support practices
	ROCK	Percent Rock in Soil Layer (1)	-	-	
	TRCL	*Tracy Loam*	20	10-30	Measured by weight
	PGSL	*Parleeville Gravelly Sandy Loam*	70	50-80	Stony
	SGSL	*Sunbury Gravelly Sandy Loam*	70	50-80	Stony
Channel Processes	CH_N(2)	Main Channel Manning's n	0.05	0.025-0.15	Low slope, stones, clean
	CH_K(2)	Channel transmission losses, hydraulic conductivity (mm/hr)	0	-	Humid, wet area.
	EVRCH	Evaporation Adjustment Factor	0	-	Assume negligible
	CH_EQN	Sediment Routing Method	0	-	Default, Simplified Bagnold Equation
	all	Channel Erosion Method	Inactive	-	Not in Scope
	PRF	Peak Rate Adjustment Factor Main Channel	1	0-2	Default
	SPCON	Sediment Transport Coefficient	0.0001	-	Default
	SPEXP	Sediment Transport Exponent	1	-	Default

Climate	ISED_DET	Maximum Half-Hour Rainfall Method	1	0,1	Monthly max, reduce variability.
	PCPMM	Monthly Average Precipitation (mm)	120 (Nov)	88-128	Affects max half hour rainfall (Marshall, 1999)
	PCPD	Monthly Precipitation Days (days)	10 (Nov)	8-10	(US WGN Station 183645)
	RAINHHMX	Monthly Maximum Half Hour Rainfall (mm/30min)	10 (Aug)	6.5-10	May be low (US WGN Station 183645)
Misc.	Plant Growth	LAI, Biomass, Residuals, etc.	Various	-	Adjusted to produce stable LAI and BIOMASS.
	BLAI	Maximum LAI (m^2/m^2)	-	-	Adjusted to maintain constant LAI
	FRST	*Mixed Forest*	5	-	
	RNGE	*Grasslands*	2.5	-	
	RNGB	*Brush lands*	3.5	-	
	BARR	*Barren lands, roads & tracks*	0.01	-	
	Management	n/a	nil	-	Removed kill/harvest ops
	Filter Strips	n/a	nil	-	Potential refinement
	Wetlands	n/a	nil	-	Potential refinement

Soil Parameters:

Layer	SOL_Z (mm)	HYDGRP	%Sand	%Silt	%Clay	SOL_BD	SOL_AWC	AWC Range	Permeability (cm/hr)	SOL_K (mm/hr)	K Range	Rock (Mass%)	DEP_IMP
Soil Type: Tracy Loam (TRCL)													
1	235	C	40	39	20	1.0	0.2	0.2-0.28	1.1	10.0	15-50	20 (L)	6000
2	750	B	50	30	17	1.3	0.12	0.12-0.24	3.5	35.0	50-150	-	-
3	1000	C	55	26	20	1.6	0.11	0.11-0.2	0.9	2.0	0.5-10	-	-
Soil Type: Parleeville Gravelly Sandy Loam (PGSL)													
1	145	B	52	29	16	1.0	0.14	0.13-0.2	28.0	30.0	50-150	70 (M-H)	6000
2	500	B	75	14	11	1.3	0.13	0.12-0.2	64.8	65.0	50-150	-	-
3	1000	A	77	14	9	1.6	0.03	0.02-0.1	7.5	73.0	30-250	-	-
Soil Type: Sunbury Gravelly Sandy Loam (SGSL)													
1	125	B	52	29	16	1.0	0.14	0.13-0.2	-	30.0	50-150	70 (M-H)	6000
2	675	B	75	14	11	1.3	0.13	0.12-0.2	-	65.0	50-150	-	-
3	1000	A	72	19	8	1.6	0.12	0.02-0.1	-	107.0	2-130	-	-

Soil Erodibility Calculations (Wall et al., 2002):

Code	A Horizon OM%	A Horizon OM% (disturbed soil OM%, min)	% Silt	% Silt and Very Fine Sand 0.05-0.1mm	% Silt and Very Fine Sand 0.05-0.1mm (max)	% Sand >0.10mm	% Sand >0.10mm (min)	% Clay	Soil Structure Class	Permeability Class
TRCL	5	0.3	39	41	47	38	32	20	2	2.5
PGSL	4	0.3	29	32	40	50	42	16	2	2
SGSL	4	0.3	29	32	40	50	42	16	2	2

**Assumed 5% sand is very fine sand (20% min/max)*

Nomograph Method

Code	USLE_K (ton/ha x ha hr/MJ mm)	Range (Grain Size)	Range (OM%)	Convert to (0.013 metric tons m^2 hr / m^3 metric ton cm)	Upper Range (0.013 metric tons m^2 hr / m^3 metric ton cm)
TRCL	0.016	0.014-0.028	0.014-0.048	0.12	0.36
PGSL	0.012	0.012-0.02	0.012-0.038	0.09	0.28
SGSL	0.012	0.012-0.02	0.012-0.038	0.09	0.28

Equation 1 (right) Method

Code	USLE_K (0.013 metric tons m^2 hr / m^3 metric ton cm)	USLE_K max (0.013 metric tons m^2 hr / m^3 metric ton cm)
TRCL	0.14	0.28
PGSL	0.11	0.23
SGSL	0.11	0.23

$$USLE_K = \frac{0.00021 \cdot M^{1.14} \cdot (12 - OM)}{100} + \frac{3.24 \cdot (c_{soilstr} - 2) + 2.5 \cdot (c_{perm} - 3)}{100}$$

$$M = (m_{silt} + m_{vfs}) \cdot (100 - m_c)$$

Equation 2 (right) Method

Code	USLE_K (0.013 metric tons m^2 hr / m^3 metric ton cm)	USLE_K max (0.013 metric tons m^2 hr / m^3 metric ton cm)
TRCL	0.13	0.18
PGSL	0.13	0.18
SGSL	0.13	0.18

$$USKE_K = \left[0.2 + 0.3 \cdot \exp(-0.256 \cdot m_s \cdot (1 - \frac{m_{silt}}{100})\right] \cdot \left[\left(\frac{m_{silt}}{m_c + m_{silt}}\right)^{0.3}\right] \cdot \left[1 - \frac{0.25 \cdot OM}{OM + \exp(3.72 - 2.95 \cdot OM)}\right] \cdot \left[1 - \frac{0.7 \cdot (1 - \frac{m_s}{100})}{\left(1 - \frac{m_s}{100}\right) + \exp(-5.51 + 22.9 \cdot (1 - \frac{m_s}{100})}\right]$$

Appendix B Land Cover Imagery

Image 1 (Left). Grasslands, barren tracks and main roads in Kerr Brook.

Image 2 (Left). Grasslands, barren tracks and main roads in Kerr Brook.

Image 3 (Left). Barren tracks, grasslands (bottom), brush lands (top) and forests (bottom center) in Kerr Brook.

Image 4 (Left). Disturbed grasslands from vehicle manoeuvres in Kerr Brook. Extended ponding in ruts on level ground.

Image 5 (Left). Rutted grasslands from vehicle manoeuvres in Kerr Brook. Extended ponding in ruts on level ground.

Image 6 (Left). Recently cleared ground for manoeuvre training in Gagetown.

Image 7 (Left). Vehicle track through brush lands during rainfall event. Tracks intercept and concentrate surface runoff. Exposed soils create erosion potential.

Image 8 (Left). Grasslands, vehicle tracks and ruts in Gagetown.

Image 9 (Left). Main road in Kerr Brook during rainfall event. Slightly rutted with long slope length.

Image 10 (Left). Hardened vehicle ford through brush land in Gagetown.

Image 11 (Left). Active bank erosion in downstream reach in Kerr Brook.

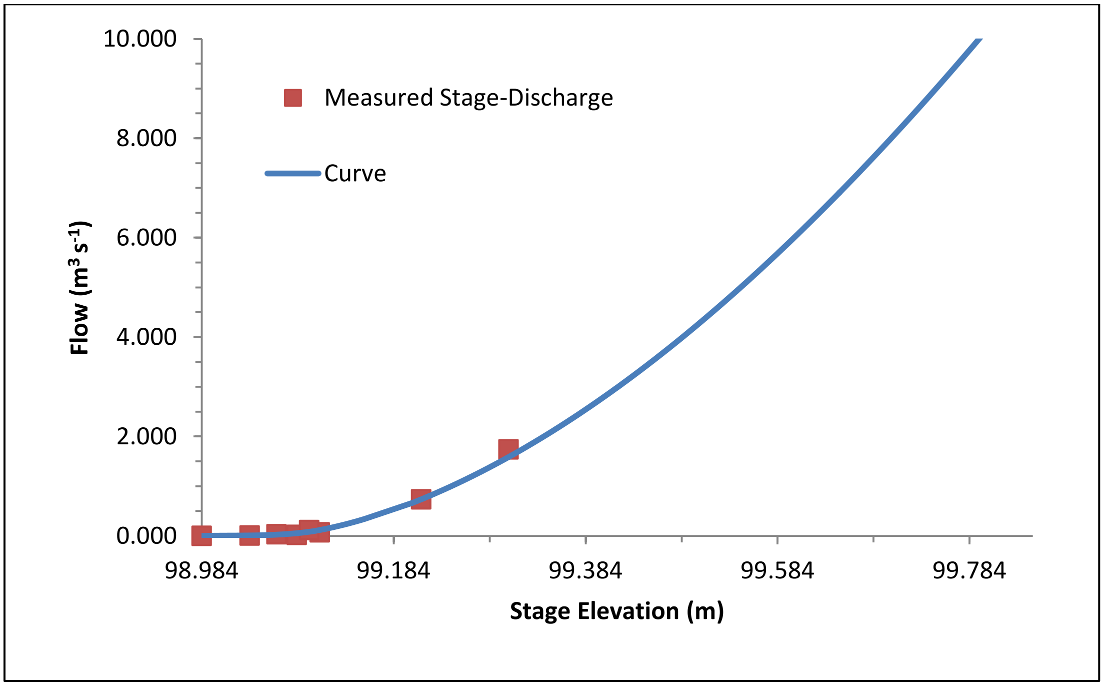
Image 12 (Left). Relatively undisturbed reach mid-stream in Kerr Brook with natural forest riparian zone.

Image 13 (Left). Bankfull discharge at mid-stream monitoring locaiton in Kerr Brook.

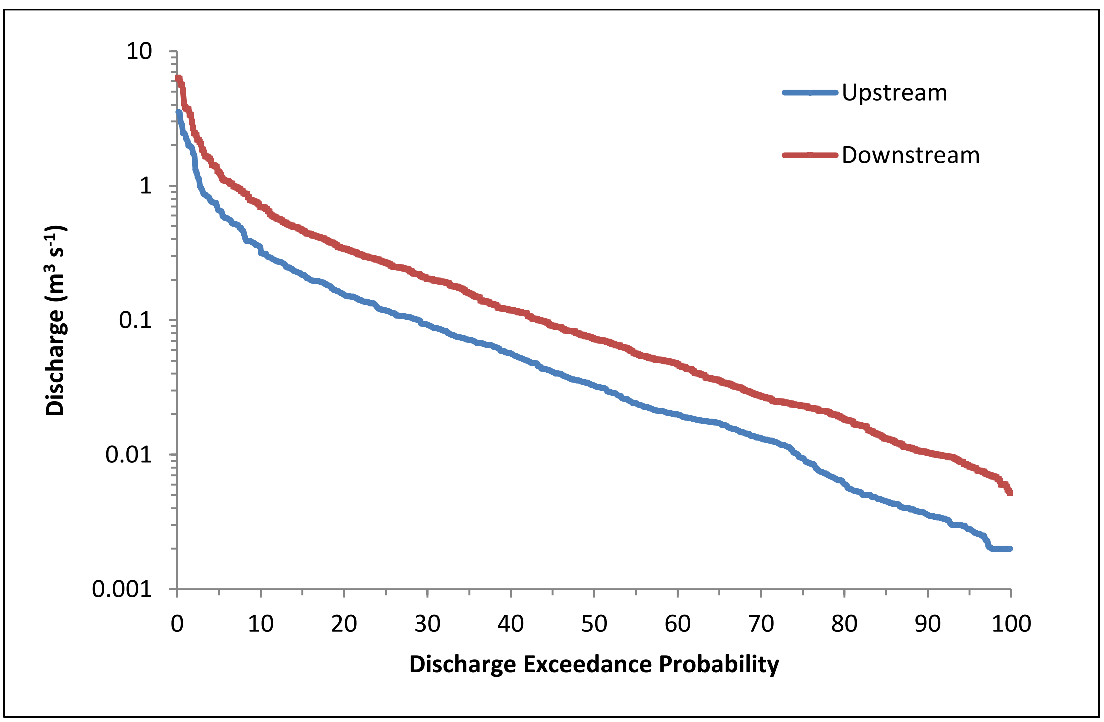
Image 14 (Left). Wetland and pond features influenced by beaver activity around brush lands and forests.

Appendix C Hydrographic Data Summary

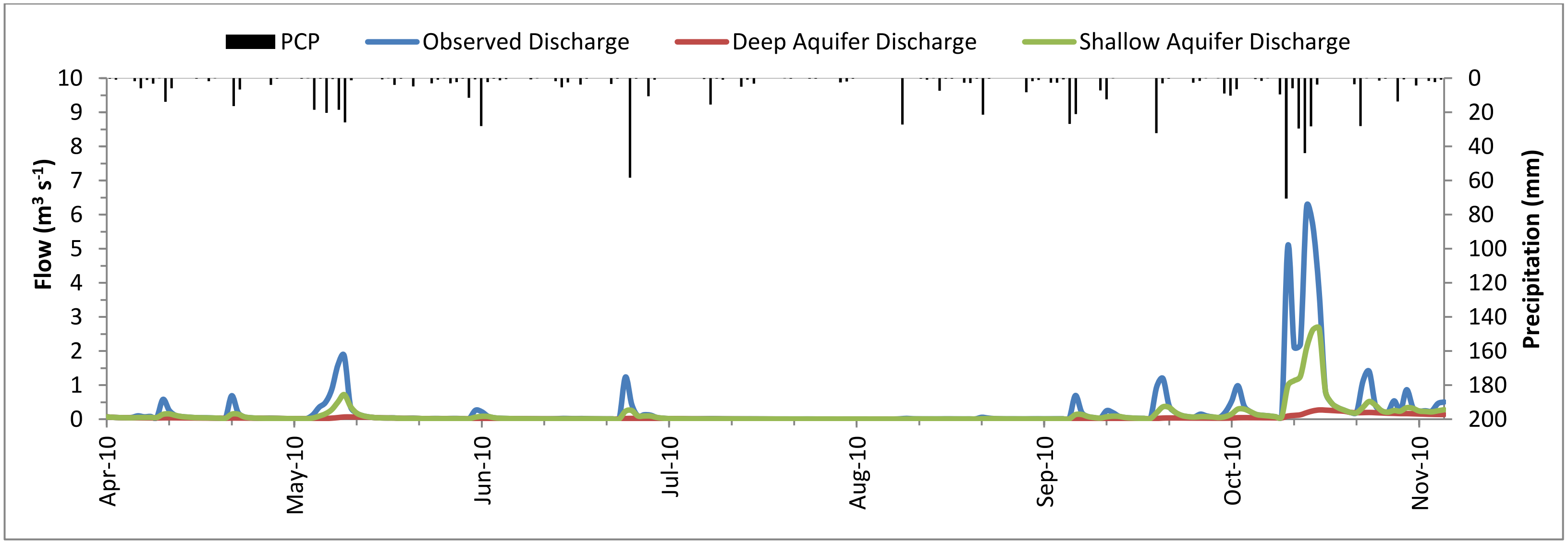
Downstream Kerr Brook Stage-Discharge Curve (Constructed by DFO):

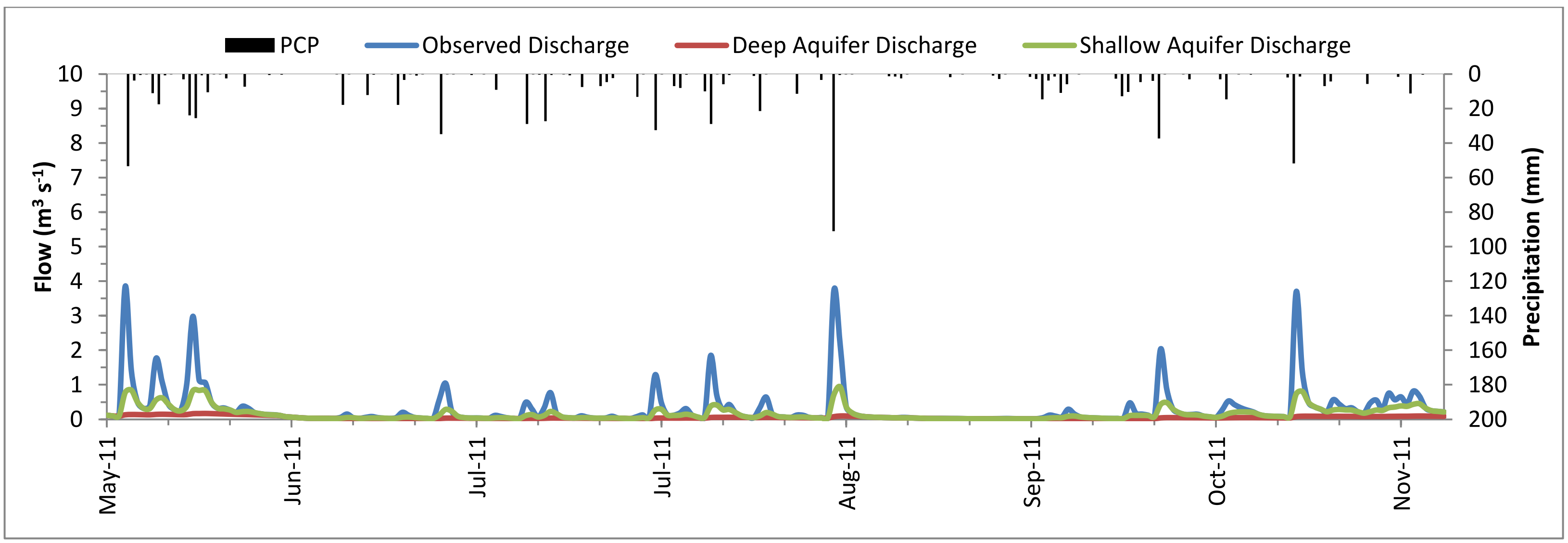


Upstream and Downstream Observed Flow-Duration Curve:

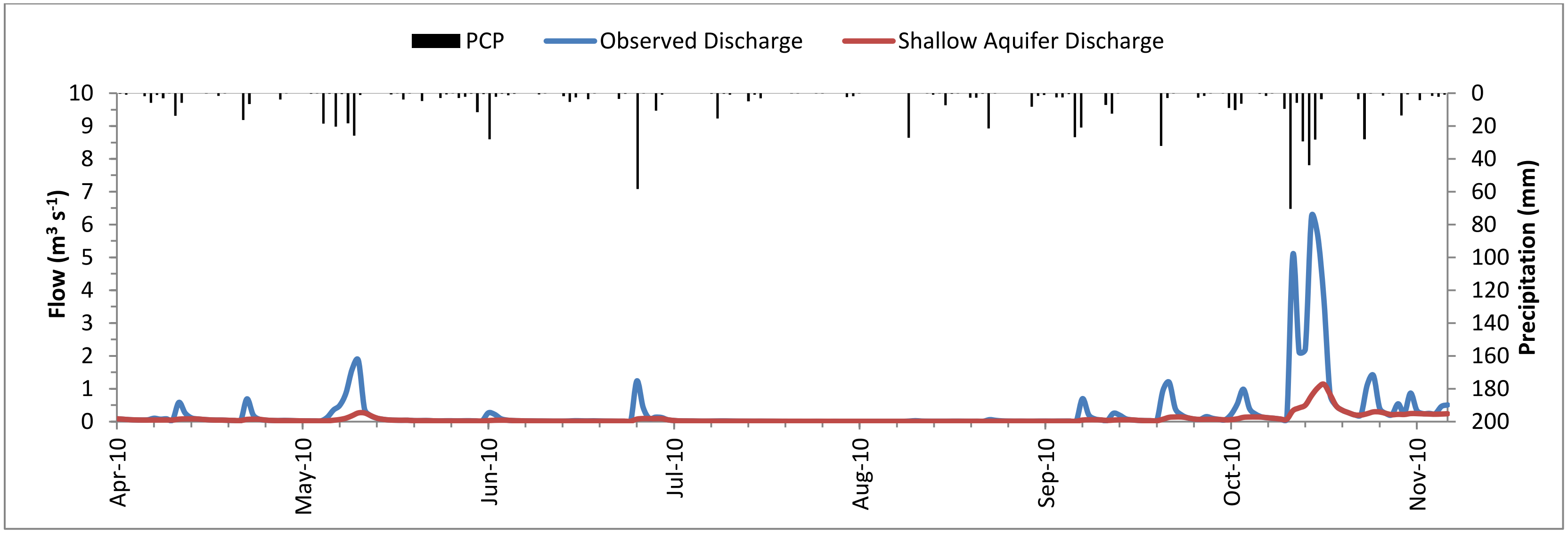


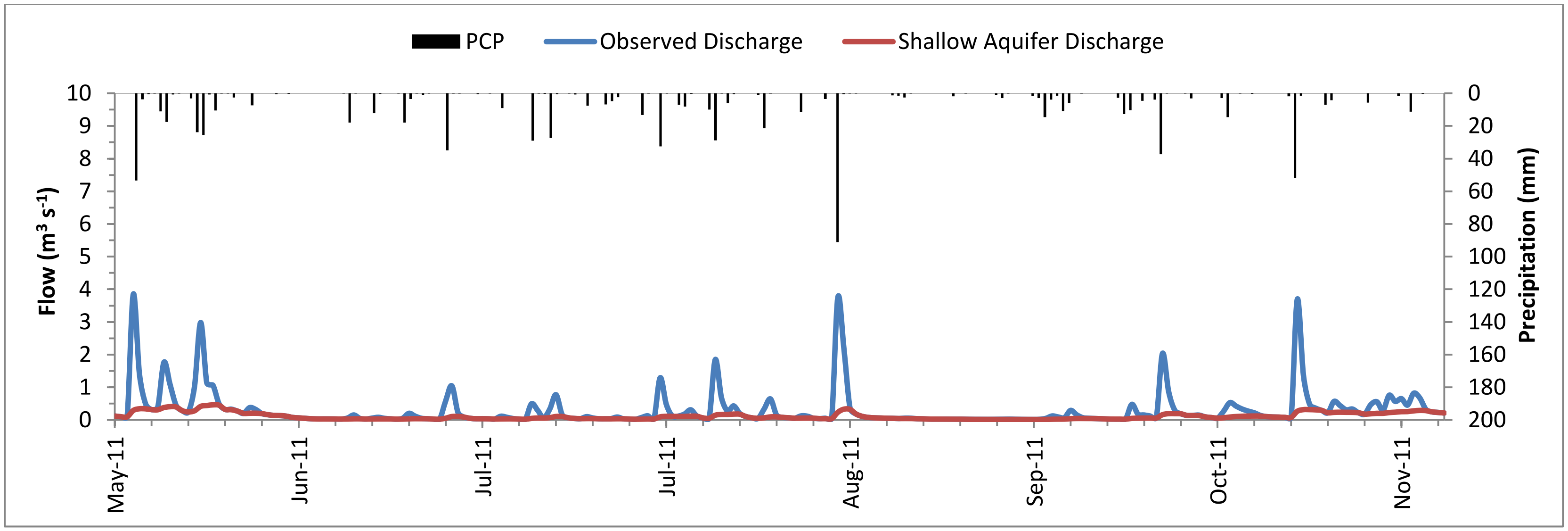
Two Component Baseflow Separation Graph:





Single Component Baseflow Separation Graph:





Appendix D Water Quality Analysis Outline

WQI - Water Quality Data:

All Data												
Total Count	702		702		710		711		-		-	
Fail Counts	304		267		5		0		-		-	
5th Mirror Trim												
Total Count	510		475		710		711		502		535	
Fail Counts	112		40		5		0		60		69	
	Ave. Turbidity	Excursion	TSS	Excursion	Temp	Excursion	pH	Excursion	Med. Turbidity	Excursion	Med. TSS	Excursion
	0.0		0.0		-0.1		6.5		0.0		0.0	
	0.0		0.0		-0.1		6.6		0.0		0.0	
	0.0		0.0		-0.1		6.7		0.0		0.0	
	0.0		0.0		-0.1		6.8		0.0		0.0	
	0.0		0.0		0.0		6.8		0.0		0.0	
	0.0		0.0		0.0		6.8		0.0		0.0	
	0.0		0.0		0.0		6.8		0.0		0.0	
	0.0		0.0		0.2		6.9		0.0		0.0	
	0.0		0.0		0.4		6.9		0.0		0.0	
	…	…	…	…	…	…	…	…	…	…	…	…

WQI - Water Quality Guidelines:

Variable	Value		Reference
Turbidity (NTU)	2.8	-	NAESI-IPS
TSS (mg L^{-1})	6.1	-	NAESI-IPS
Temp (°C)	24	-	Raleigh, 1982
pH	6.5	9	CCME CEQG

WQI - Mirror 5th Percentile Trim:

Value	Turbidity (Ave., NTU)	Turbidity (Med., NTU)	TSS (Ave., mg L^{-1})	TSS (Med., mg L^{-1})	Temperature (°C)	pH
5th percentile	0.0	0.0	0.0	0.0	2.6	-
Median	2.4	1.8	4.4	4.1	15.0	-
Upper Limit	4.7	3.6	8.9	8.2	27.4	-

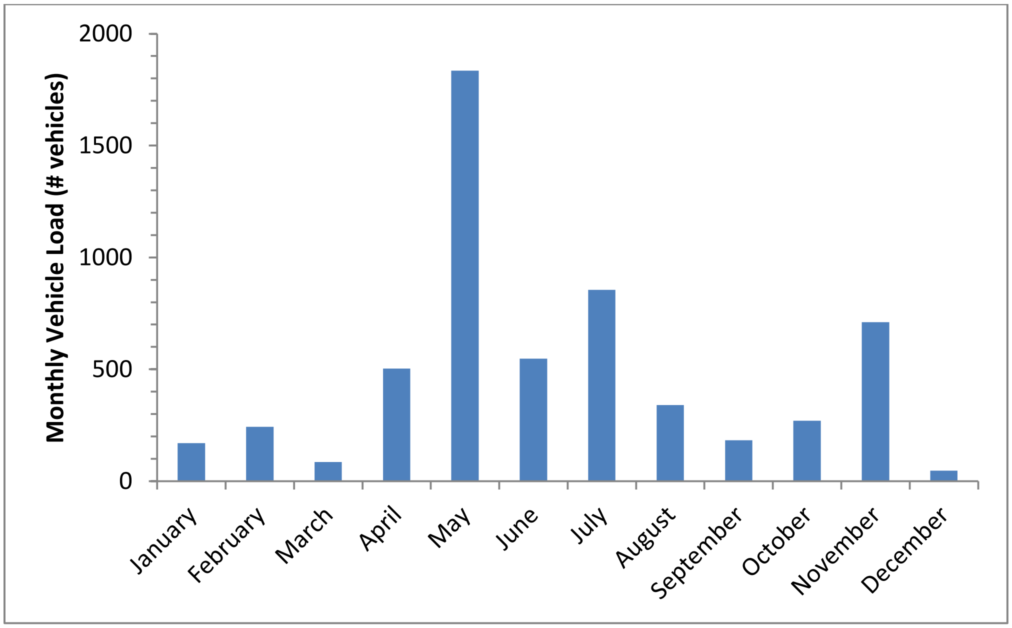
WQI - Results for Average Daily Turbidity with Mirror 5th Percentile Trim (CCME, 2001):

F1	75.00
F2	6.53
nse	0.02
F3	2.17

WQI	57

Marginal

Kerr Brook Monthly Average Vehicle Load:

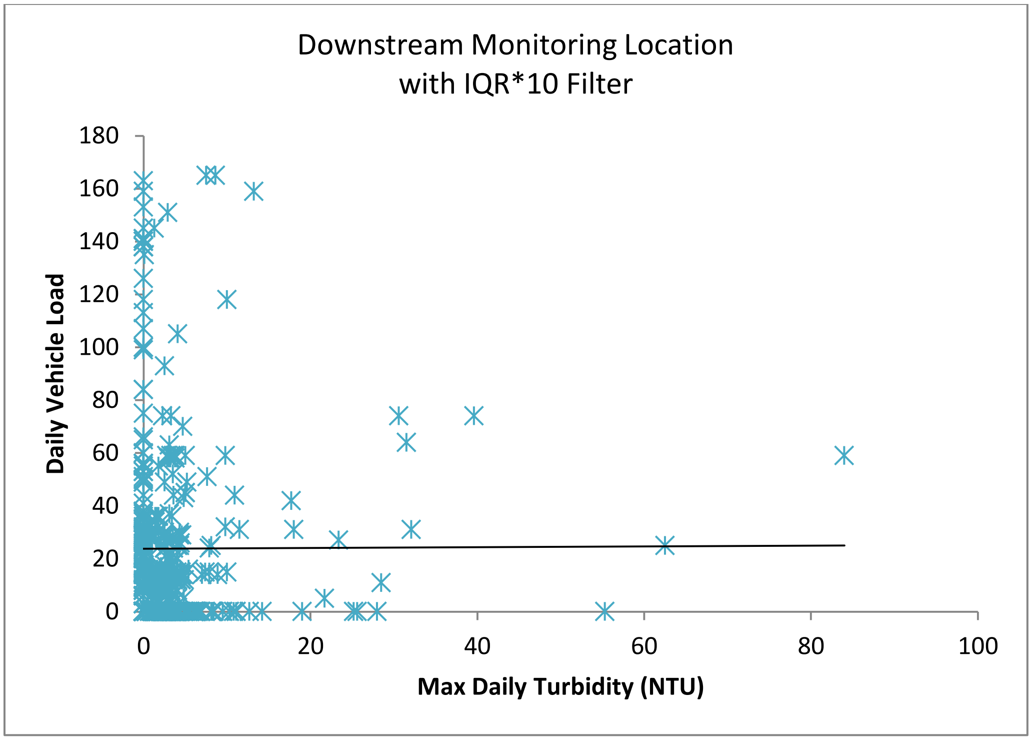


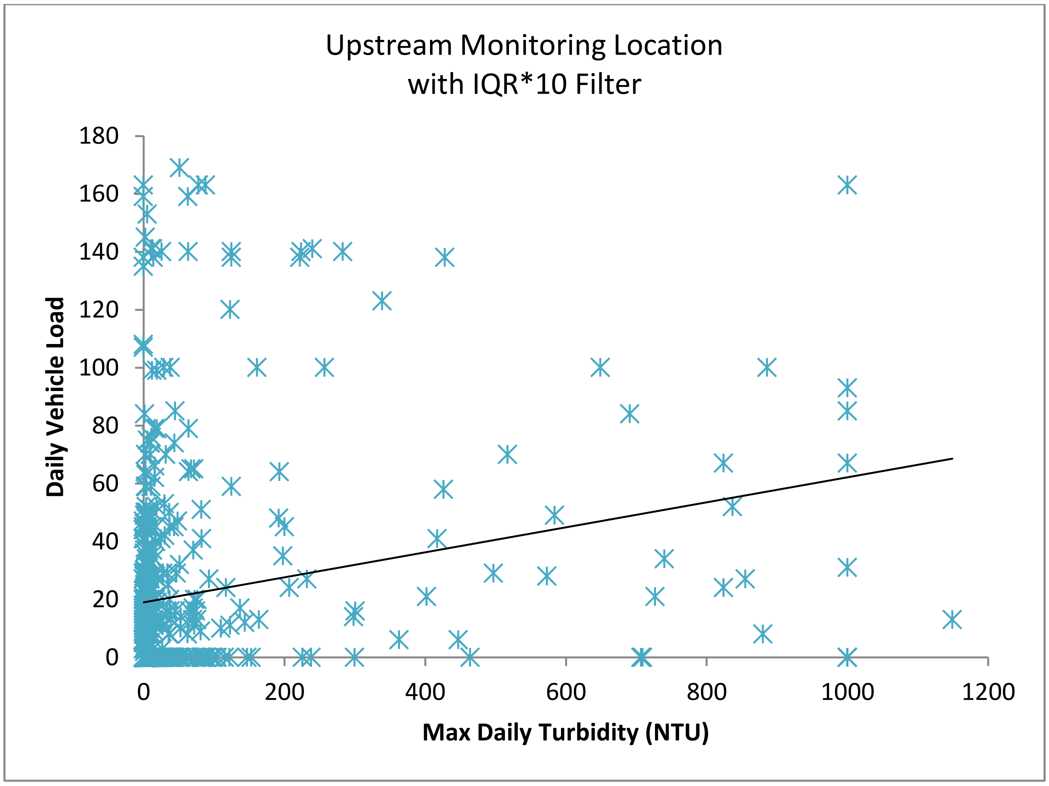
Daily Vehicle Load and Daily Turbidity Statistic Correlation:

Raw Data	Correlation Coefficient				
	Daily Statistic				
Location	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Upstream	0.05	0.05	0.03	0.05	0.22
Downstream	-0.14	-0.10	-0.03	-0.02	0.03

10xIQR Filter	Correlation Coefficient				
	Daily Statistic				
Location	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Upstream	0.05	0.05	0.03	0.05	0.22
Downstream	-0.14	-0.10	-0.03	-0.02	0.02

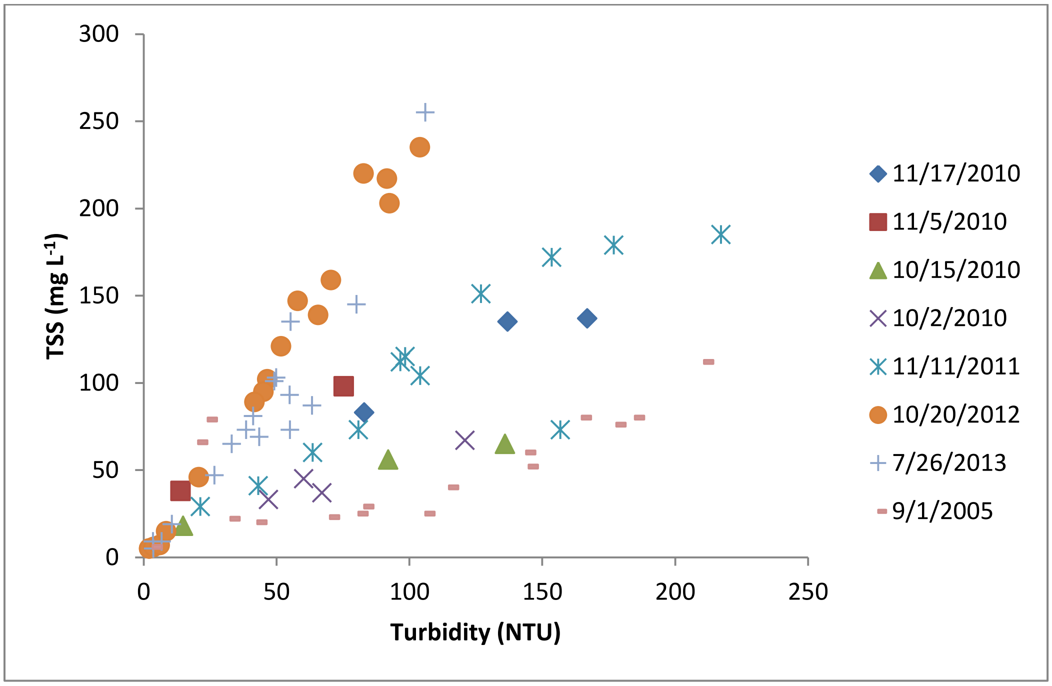
Maximum Daily Turbidity and Daily Vehicle Load Graph:



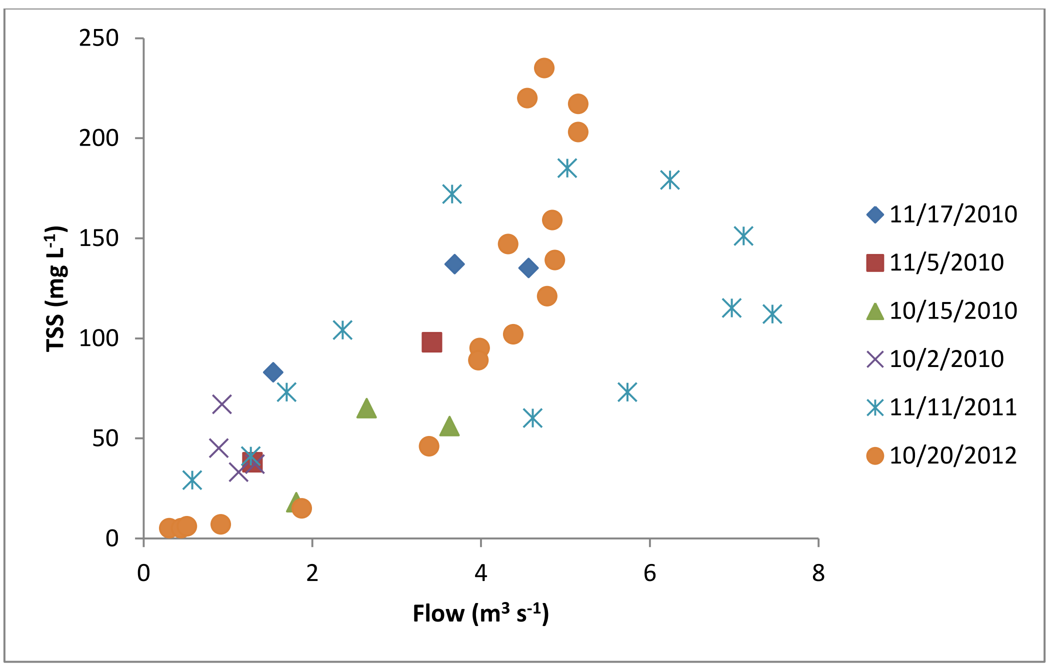


Appendix E Suspended Sediment Regression Analysis Summary

Downstream Turbidity and TSS Observations:



Downstream Flow and TSS Observations:



Turbidity, Flow and TSS Regression Summary Output:

Regression Statistics	
Multiple R	0.79
R Square	0.63
Adjusted R^2	0.61
Std. Error	41.50
Observations	42

ANOVA	*df*	*SS*	*MS*	*F*	*Sig.F*
Regression	2	112813	56406	32.75	0.00
Residual	39	67177	1722		
Total	41	179990			

	Coeff.	*Std. Error*	*t Stat*	*α*	*Lower 95%*	*Upper 95%*	*Lower 90.0%*	*Upper 90.0%*
Intercept	2.61	12.92	0.20	0.84	-23.52	28.74	-19.15	24.37
X1 Turbidity	0.41	0.15	2.76	0.01	0.11	0.72	0.16	0.67
X2 Flow	17.99	3.89	4.62	0.00	10.12	25.86	11.44	24.55

Trial Regression Results Summary:

Turbidity Data Only	
Multiple R	0.51
R Square	0.26
Adjusted R^2	0.25
Std. Error	52.77
Observations	74

Flow Data Only	
Multiple R	0.74
R Square	0.55
Adjusted R^2	0.54
Std. Error	44.79
Observations	42

All Variables	
Multiple R	0.86
R Square	0.73
Adjusted R^2	0.70
Std. Error	36.46
Observations	42

All Variables	*Coeff.*	*Std. Error*	*t Stat*	*α*
X1 Turbidity	0.66	0.17	3.90	0.00
X2 Flow	16.18	4.33	3.74	0.00
X3 Rise/Fall	16.50	14.06	1.17	0.25
X4 Dry Days	-3.40	2.44	-1.40	0.17
X5 Vehicles	-0.07	0.05	-1.50	0.14

Appendix F Automated Sensitivity Analysis and Calibration Summary

Initial GLUE Summary: (*t-stat ranked for P<0.1, *Range Type: A-Absolute; V-Replace; and R-Relative)

Simulation:	Sim1	Sim1
Trial:	G.1	G.2
Simulation #:	10000	10000
Observations:	DS	DS/US
Obj. Function:	NSE	NSE
Obj. Threshold:	0.65	0.75
Beh. Solutions:	2071	83
P-Factor (US/DS):	0.83	0.55 / 0.82
R-Factor (US/DS):	0.53	0.29 / 0.46
NSE (US/DS):	0.79	0.81 / 0.78
R^2 (US/DS):	0.80	0.82 / 0.79

Parameter	Final Range Adjustment	Best Value	t-Stat Rank (P<0.1)	Final Range Adjustment	Best Value	t-Stat Rank (P<0.1)	Initial Value	Initial Range	Range Method
CN2 FRST-TRCL/PGSL	-24.9 - 12.9	-19.7	9	-24.9 - 12.9	1.8	-	70	-25 - +13	A
CN2 RNGE-TRCL/PGSL	-45.8 - 2.5	-10.3	7	-45.8 - 2.5	-39.1	7	86	-49 - +3	A
CN2 RNGB-TRCL/PGSL	-24.8 - 11.3	-19.8	-	-24.8 - 11.3	1.9	8	70	-26 - +13	A
CN2 BARR-TRCL/PGSL	-11.5 - 5.5	-4.9	11	-11.5 - 5.6	1.4	11	88	-12 - +6	A
CNCOEF	0.50 - 2.00	1.99	5	0.53 - 1.98	1.94	3	1	0.5 - 2	V
CANMX	-2.00 - 2.00	-1.74	4	-1.99 - 1.72	-1.7	2	0-4	-2 - +2	A
EPCO	-0.2 - 0.2	0.17	-	-0.20 - 0.20	-0.17	-	0.4-0.8	-0.2 - +0.2	A
ESCO	0.05 - 1.00	0.67	10	0.50 - 0.99	0.98	13	0.95	0.5 - 1	V
SURLAG	1.0 - 10.0	1.13	3	1.0 - 9.0	1.1	5	4	0 - 10	V
OV_N	-0.50 - 0.50	0.39	12	-0.35 - 0.50	-0.1	12	0.02-0.3	-0.5 - +0.5	R
GW_DELAY	0.00 - 5.00	3.63	2	0.00 - 4.87	2.7	4	0.25	0 - 5	V
ALPHA_BF	0.50 - 1.00	0.93	8	0.50 - 0.99	0.87	9	0.9	0.7 - 1	V
GW_REVAP	0.02 - 0.20	0.18	-	0.02 - 0.20	0.06	-	0.02	0.02 - 0.2	V
RCHRG_DP	0.00 - 0.20	0.13	-	0.00 - 0.20	0.01	-	0.05	0 - 0.2	V
SOL_K	-0.50 - 0.50	-0.16	13	-0.46 - 0.50	-0.24	10	2-70	-0.5 - +0.5	R
SOL_Z	-0.50 - 0.50	0.46	6	-0.50 - 0.47	-0.04	6	0-1000	-0.5 - +0.5	R
SOL_AWC	-0.20 - 0.20	-0.17	-	-0.19 - 0.19	-0.09	-	0.1-0.28	-0.2 - +0.2	R
DEP_IMP	1005 - 6000	2560	1	1032 - 5973	1157	1	6000	1000 - 6000	V

Final GLUE Summary: (*t-stat ranked for P<0.1, *Range Type: A-Absolute; V-Replace; and R-Relative)

Simulation:	Sim(r4)	Sim(r4)
Method:	GLUE	GLUE
Trial:	G.3.1	G.3.2
Simulation #:	10000	10000
Observations:	DS	US/DS
Obj. Function:	NSE	NSE
Obj. Threshold:	0.80	0.80
Beh. Solutions:	5665	4345
P-Factor (US/DS):	0.51	0.07 / 0.12
R-Factor (US/DS):	0.36	0.07 / 0.09
NSE (US/DS):	0.88	0.82 / 0.87
R^2 (US/DS):	0.88	0.83 / 0.88

Parameter	**Final Range Adjustment**	**Best Value**	**t-Stat Rank (P<0.1)**	**Final Range Adjustment**	**Best Value**	**t-Stat Rank (P<0.1)**	**Initial Value**	**Initial Range**	**Range Method**
CN2 (all/TRCL)	-8-8	-6.4	3	-8-8	6.8	-	73-86	-8-8	A
CN2 (PGSL)	-	-	-	-8-8	0.7	-	73-86	-8-8	A
CNCOEF	2-0.5	1.05	4	0.5-1.5	0.56	1	1.55	0.5-2	V
DEP_IMP (all/TRCL)	1000-6000	4385	6	1000-6000	4565	-	6000	1000-6000	V
DEP_IMP (PGSL)	-	-	-	1000-6000	1885	-	6000	1000-6000	V
ALPHA_BF	0.85-0.94	0.87	-	0.85-0.95	0.9	6	0.99	0.85-0.95	V
WET_NVOL ($10^4 m^3$)	-1-1	0.32	5	-1-1	0.85	5	10	-1-1	R
WET_MXVOL ($10^4 m^3$)	-1-1	-0.96	1	-1-1	-0.92	2	20	-1-1	R
WET_K (mm/hr)	0-1	0.97	2	0-1	0.78	3	0.5	0-1	V
RCHRG_DP	-0.2-0.2	0.028	7	-0.2-0.2	0.16	4	0.35	-0.2-0.2	R

Appendix G Manual Calibration Summary

Simulation:	Sim1		Sim(t50)		Sim(t85)		Sim(r4)	
Year:	2010	2011	2010	2011	2010	2011	2010	2011
DS Total Flow %d:	-80	-70	-4	2	-2	0	-2	-2
DS SURQ %d:	88	85	-3	-1	-10	2	-11	-2
DS GW/LATQ %d:	-463	-332	-7	5	14	3	10	-2
DS DA_RCHRG %d:	-	-	-	-	-	-	2	1
DS NSE:	0.24	-0.55	0.89	0.82	0.81	0.81	0.79	0.73
DS R^2:	0.8	0.8	0.9	0.82	0.86	0.63	0.88	0.86
US Total Flow %d:	24	37	12	33	12	30	7	21
US SURQ %d:	58	65	10	29	-2	19	-2	18
US GW/LATQ %d:	-26	-16	14	33	44	43	23	25
US DA_RCHRG %d:	-	-	-	-	-	-	42	44
US NSE:	0.83	0.58	0.85	0.71	0.85	0.79	0.81	0.83
US R^2:	0.84	0.69	0.88	0.79	0.85	0.84	0.83	0.84

Parameters	**Initial Value**	**Final Values**	**Final Values**	**Final Values**
CN2 FRST-TRCL	70	**77**	**79**	**75**
CN2 FRST-PGSL	55	**67**	**77**	**73**
CN2 RNGE-TRCL	86	**93**	**89**	**85**
CN2 RNGE-PGSL	79	**91**	**86**	**82**
CN2 RNGB-TRCL	70	**77**	**83**	**79**
CN2 RNGB-PGSL	56	**68**	**77**	**73**
CN2 BARR-TRCL	88	**90**	**91**	**86**
CN2 BARR-PGSL	84	**90**	**91**	**86**
CNCOEF	1	**1.55**	1.55	1.55
CANMX (mm) FRST	4	4	4	4
CANMX (mm) RNGE	1	1	1	1
CANMX (mm) RNGB	2	2	2	2
CANMX (mm) BARR	0	0	0	0
EPCO FRST	0.8	**0.6**	0.6	0.6
EPCO RNGE	0.6	**0.4**	0.4	0.4
EPCO RNGB	0.7	**0.5**	0.5	0.5
EPCO BARR	0.4	**0.2**	0.2	0.2
ESCO	0.95	0.97	0.95	0.95
SURLAG	4	1	1	1
GW_DELAY (days)	0.25	0	0	0
ALPHA_BF ($days^{-1}$)	0.9	**0.99**	0.99	0.99
GW_REVAP	0.02	0.025	0.02	0.02
RCHRG_DP	0.05	0	0	**0.35**
SOL_K (mm/hr)	2-70	**4-140**	4-140	4-140
SOL_Z (mm)	1000	1000	1000	1000
SOL_AWC TRCL	0.11-0.2	**0.1-0.18**	0.1-0.18	0.1-0.18
SOL_AWC PGSL	0.03-0.14	**0.03-0.14**	0.03-0.14	0.03-0.14
DEP_IMP 0-4.5 slope	6000	**3000**	3000	6000
DEP_IMP 4.5-6.5 slope	6000	**3000**	3000	6000
DEP_IMP 6.5-99 slope	6000	**3000**	**6000**	6000

Remarks:

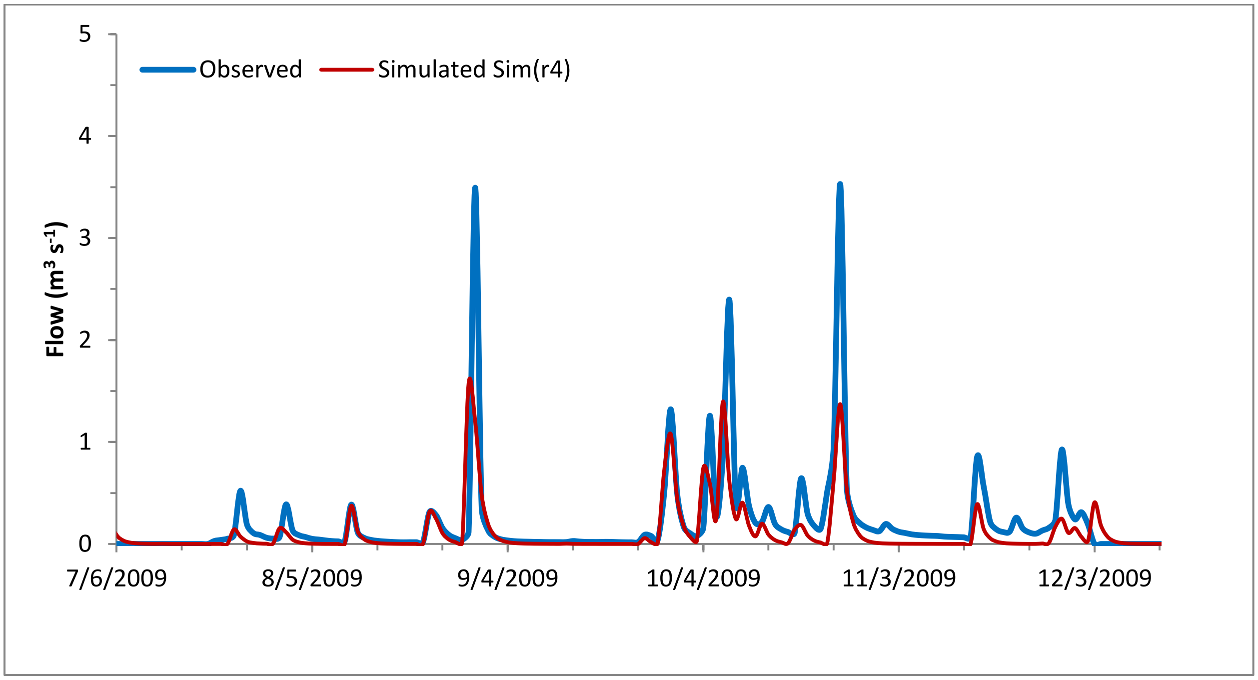
*Sim(t85) and Sim(r4) wetland parameters

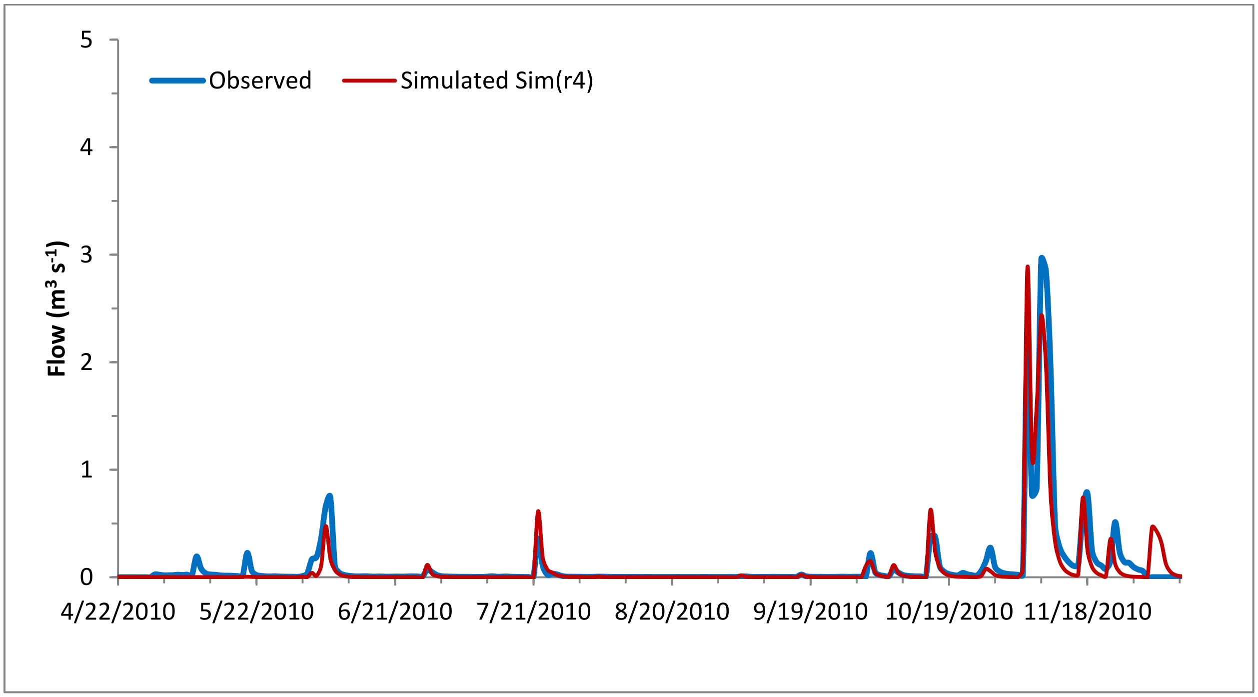
SB	3
WET_FR	0.4
WET_NSA	20
WET_NVOL	10
WET_MXSA	25
WET_MXVOL	20
WET_K	0.5
WETEVCOEF	0.6

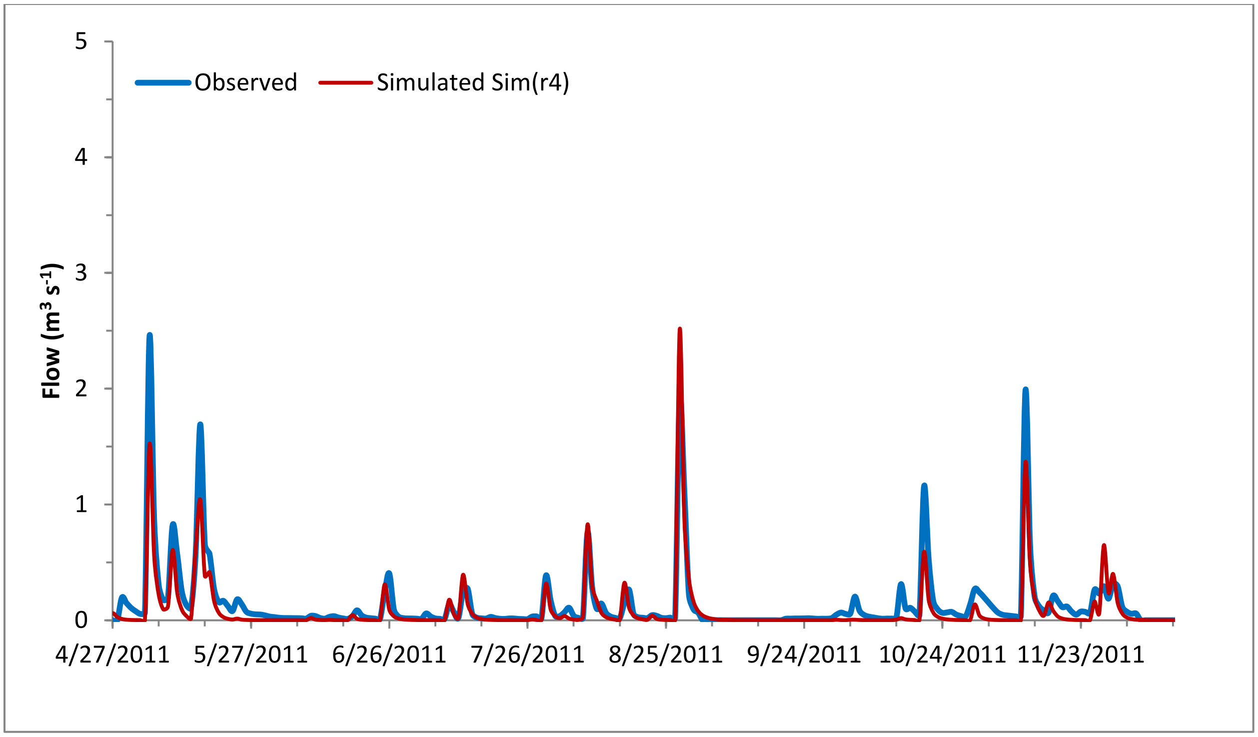
*Graphical presentation improved by Sim(t85)

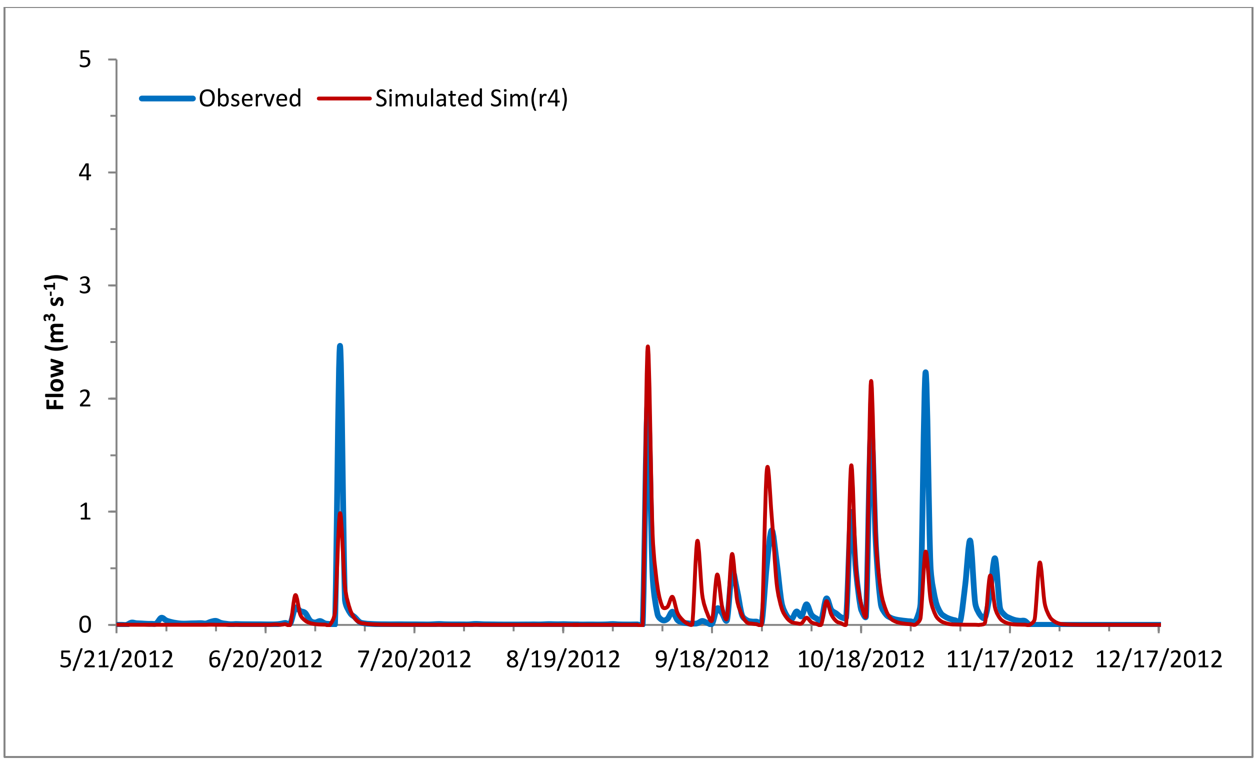
Appendix H   Upstream Results

Upstream daily discharge:

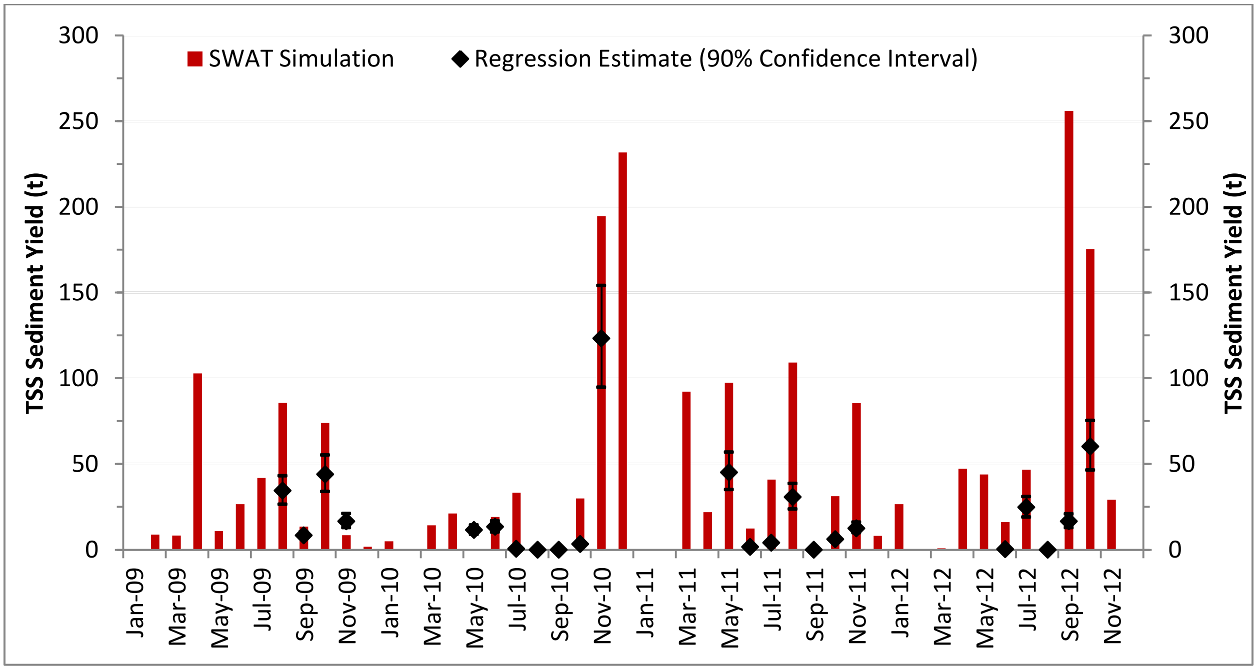





5
4
3
2
1
0
Flow (m³ s⁻¹)
Observed
Simulated Sim(r4)
4/27/2011
5/27/2011
6/26/2011
7/26/2011
8/25/2011
9/24/2011
10/24/2011
11/23/2011


5
4
3
2
1
0
Flow (m³ s⁻¹)
Observed
Simulated Sim(r4)
5/21/2012
6/20/2012
7/20/2012
8/19/2012
9/18/2012
10/18/2012
11/17/2012
12/17/2012

Upstream monthly sediment yield: (regression intercept set to zero for upper and lower limits)



Appendix I Journal Article Pending Publication

Journal Article Submitted To: Water Quality Research Journal of Canada

Submitted: April 2014

Title: Applying the Soil Water Assessment Tool to 5th Canadian Division Support Base Gagetown

Abbreviated Title: Applying SWAT to 5 CDSB Gagetown

Authors: **Shawn Burdett[1]**

Michael Hulley[2]

Andy Smith[3]

Addresses: [1]shawn.m.burdett@gmail.com, 613-331-6131. Department of Civil Engineering, Royal Military College of Canada, Kingston, Ontario, Canada.

Alternate Contact: [2]Michael.Hulley@rmc.ca, 613-541-6000 ext 6393. Department of Civil Engineering, Royal Military College of Canada, Kingston, Ontario, Canada.

Alternate Contact: [3]Andy.Smith@forces.gc.ca, 506-357-5220, Environmental Service Branch, 5th Canadian Division Support Base Gagetown, Oromocto, New Brunswick, Canada.

Abstract

A hydrologic and water quality model is sought to establish an approach to land management decisions for a Canadian Army training base. Training areas are subjected to high levels of persistent activity creating unique land cover and land-use disturbances. Deforestation, complex road networks, off-road manoeuvres, and vehicle stream-crossings are among major anthropogenic activities observed to affect these landscapes. Expanding, preserving and improving the quality of these areas to host training activities for future generations is critical to maintain operational effectiveness. Inclusive to this objective is minimizing resultant environmental degradation, principally in the form of hydrologic fluctuations, excess erosion, and sedimentation of aquatic environments. In some situations these impacts (particularly sedimentation) could be considered a violation of environmental legislation, such as the *Fisheries Act*.

Application of the Soil Water Assessment Tool (SWAT) was assessed for its ability to simulate hydrologic and water quality conditions observed in military landscapes at 5th Canadian Division Support Base (5 CDSB) Gagetown, New Brunswick. Despite some limitations, this model adequately simulated three partial years of daily watershed outflow (NSE=0.47-0.79, R^2=0.50-0.88) and adequately predicted suspended sediment yields during the observation period (%d=6-47 %) for one highly disturbed sub-watershed in Gagetown. Further development of this model may help guide decisions to develop or decommission training areas, guide land management practices and prioritize select landscape mitigation efforts.

Key words: Hydrology; Erosion; SWAT; Military; Water Quality; Modelling

Introduction

Developing an understanding of watershed hydrology and land cover is a critical component to the successful assessment of stream flow and water quality conditions. Landscape alterations can contribute significant non-point source pollutants to aquatic environments and markedly alter watershed hydrology (Stanley and Arp 2002; Culp et al. 2009; Winter et al. 1998). The principal objective of this study was to assess the effectiveness and suitability of a numerical model on a watershed used extensively for Army exercises. Should this prove successful, continued expansion and applications may then guide landscape alterations and mitigation efforts to achieve targeted water quantity and quality guidelines for aquatic environments.

Anthropogenic activities, such as agricultural cultivation, urban development and deforestation, can significantly impacts watershed health. These activities may shift water yields, increase peak flows, degrade water quality and cause a variety of other detrimental impacts (Winter et al. 1998). Knowledge of hydrologic impacts and non-point source sediment pollution from military training grounds is relatively limited compared to more common and conventional landscapes across Canada. Increased surface runoff, decreased baseflow, elevated erosion rates, increased sediment yields and increased stresses to aquatic environments have been identified as watershed management issues at 5 CDSB Gagetown (Smith 2014). At this time, Gagetown is undertaking a multi-year, multi-million dollar project to address some of these issues under the Sediment and Erosion Control Plan.

Many environmental models have been recommended, developed or applied to assist land managers in mitigating detrimental watershed impacts on military lands. Regression equations have been developed to relate climate, land cover and land-use variables to stream water quality conditions at Fort Stewart, Georgia (Jager et al. 2011). Some tools rely on lumped geographic and climate variables to predict surface erosion, such as the empirical Universal Soil Loss Equation (USLE) and its derivatives. Various forms of this model have been applied to several military installations in the United States of America (US) (Warren et al. 1989; Wigmosta et al. 2007; Dalton 2008). These studies typically establish annual erosion estimate but do not always consider the redistribution of sediments across the landscape and transport within stream channels. Other, more process-based models, account for sediment transport and deposition patterns, as seen in the Unit Stream Power Erosion Deposition (USPED) model, EROSION 3-D and the Hillslope Erosion Model. These models have seen applications to military landscapes in Germany and the US in order to predict general erosion and deposition trends or event-based water and sediment dynamics (Deinlein and Böhm 2000; Warren et al. 2005; Liu et al. 2007; Steichen et al. 2008). The Water Erosion Prediction Project (WEPP) is another modelling tool that has been used for military watersheds (Gaffer et al. 2008). WEPP has also been integrated into multi-spatial scale, hybrid modelling projects for military installations to quantify detailed processes, such as road erosion (Donigian et al. 2010). While these latter models primarily focus on surface runoff, the Distributed Hydrology Soil Vegetation Model (DHSVM), Hydrological Simulations Program-Fortran (HSPF) and SWAT have been used as more holistic watershed models for military lands in order to predict continuous stream flow and water quality conditions (Wigmosta et al. 2007; Dalton 2008; Donigian et al. 2010).

The classical USLE only accounts for lumped monthly or annual erosion rates. The USPED model enhances the USLE capabilities by accounting for distributed flow accumulation, profile curvature and transport-limited sediment deposition (Warren et al. 2005). Both these models lack detailed hydrological considerations and only focus on landscape processes. WEPP, while generally applied at the hillslope scale, accounts for more physically-based dynamic conditions. This includes soil detachment from raindrops and flow shear stress, sediment deposition, soil physics, plant growth and management conditions (Flanagan et al. 2013). The previously mentioned models may be distributed but they do not consider variations in micro topography, such as vehicle ruts and road features. The Limburg Soil Erosion Model (LISEM) accounts for some of these limitations with sub-cell rut coverage and other features (Roo et al. 1996). WEPP can be modified to account for road features, such as cut-slopes, ditches and ruts. Detailed overland flow, ditch drainage and cut-slope water interception, can also be simulated in the DHSVM (Beckers et al. 2009).

Hydrology, erosion and water quality models vary in data requirements, conceptual framework, complexity and outputs. The simulated time-scale of watershed models can range from hours to decades with computational time-steps varying from seconds to years. Observed climate data, event-based design storms or stochastic weather generators can be used to drive model computations. Spatial distributions have included cells a few meters in size, field scale hillslope elements or relatively large sub-catchments. Agricultural watersheds can typically utilize lumped or semi-distributed landscape characteristics because of their natural homogeneity. Forested watersheds typically require more distributed representations due to the significant influences of forestry roads on sediment yields (Luce et al. 2001). Military training areas display characteristics from both these land-use categories and are recognized to require multiple spatial scales for watershed modelling assessments (Donigian et al. 2010).

SWAT, the model selected for this study, operates on a daily time-step and has a strong capacity to process decades of data. Watersheds are simulated with distributed sub-basins and lumped Hydrological

Response Units (HRU) composed of unique land cover, slope and soil conditions. Runoff is calculated with the SCS CN method, or Green and Ampt Infiltration method. There are several evapotranspiration (ET) options, including the Penman-Monteith method which accounts for daily temperature, relative humidity, wind speed and solar radiation. Vertical and lateral groundwater flow is calculated through multiple soil layers over one groundwater reservoir. Erosion is calculated with the empirical Modified USLE and sediments, along with water, can be routed through a series overland and channels structures.

Army training grounds are affected by intense off-road vehicle activity, as well as a variety of other operations and land management practices. Heavily utilized areas are often intermixed with relatively undisturbed, natural environments. Within the US, many training areas are located in semi-arid locations and are generally subject to intense usage. Training activities and poor land management practices can cause vegetation and soil loss leading to substantial environmental degradation, reduced training effectiveness and costly rehabilitation efforts (Dalton 2008; Stevens et al. 2008).

The training area at 5 CDSB Gagetown, has challenges that are both common and unique to bases in the US from the previously referenced studies. Humid, wet conditions can make soils more susceptible to rutting, compaction and disturbances. Vegetation management (e.g. cutting, spraying or burning) is required to maintain manoeuvre corridors in a grassland or 'old field' state. Cold climate conditions have significant effects on watershed processes and training activity. Water quality and channel stability are also a concern, including point source sediment inputs from vehicle stream crossing activities and flow regime fluctuations from deforestation and land cover change.

Military vehicle traffic, and the effect it has on the landscape, has received considerable attention because the effects can directly influence watershed hydrology, erosion and water quality conditions. USLE cover-factors have been predicted based on vehicle manoeuvre impact miles per hectare at Camp Atterbury, Indiana (Dalton 2008). Cover-factors for manoeuvre lands have also been developed considering LANDSAT imagery and vegetation field surveys (Warren et al. 2005; Warren et al. 1989). Vegetation loss and rut depth from vehicle manoeuvres have been estimated with the Vehicle Dynamic Monitoring and Tracking System which considers detailed vehicle properties, movement tracking dynamics and soil properties (Koch et al. 2012). A field trafficability model has also been developed for 5 CDSB Gagetown, utilizing the Forest Hydrology Model, soil information and basic vehicle properties (Vega-Nieva et al. 2008). These tools have the potential to be integrated with broad-based hydrology and water quality models to maximize their effectiveness.

Study Area

5 CDSB Gagetown is located in Southern New Brunswick and is one of the largest military training facilities in Canada, with an area of over 1,100 km^2 (Figure 1). This includes 21,000 ha of manoeuvre areas, 30,000 ha of ranges and impact areas, 829 km of roads, 362 km of off-road trails, more than 500 fords and 1,174 in-stream culverts and bridges. Primary land cover categories can be described as forested (66 %), grasslands and early succession (18 %), aquatic environments (10 %) and barren areas (6 %). Generally, grasslands are highly disturbed from off-road vehicle manoeuvres and include dense track networks. Barren areas include roads, recently devegetated areas being converted to grasslands and areas that are persistently barren with negligible vegetation due to repetitive vehicle traffic.

The base was established in the 1950's, which involved the expropriation of private lands including several communities, agricultural areas and forest harvest blocks. Additional land was deforested to create the manoeuvre fields, ranges and munition impact areas at this time. In the 1990's another 7,000 ha of forests were cleared in an attempt to create more manoeuvre areas; however, many of these areas were not used for years because of erosion and vegetation issues.

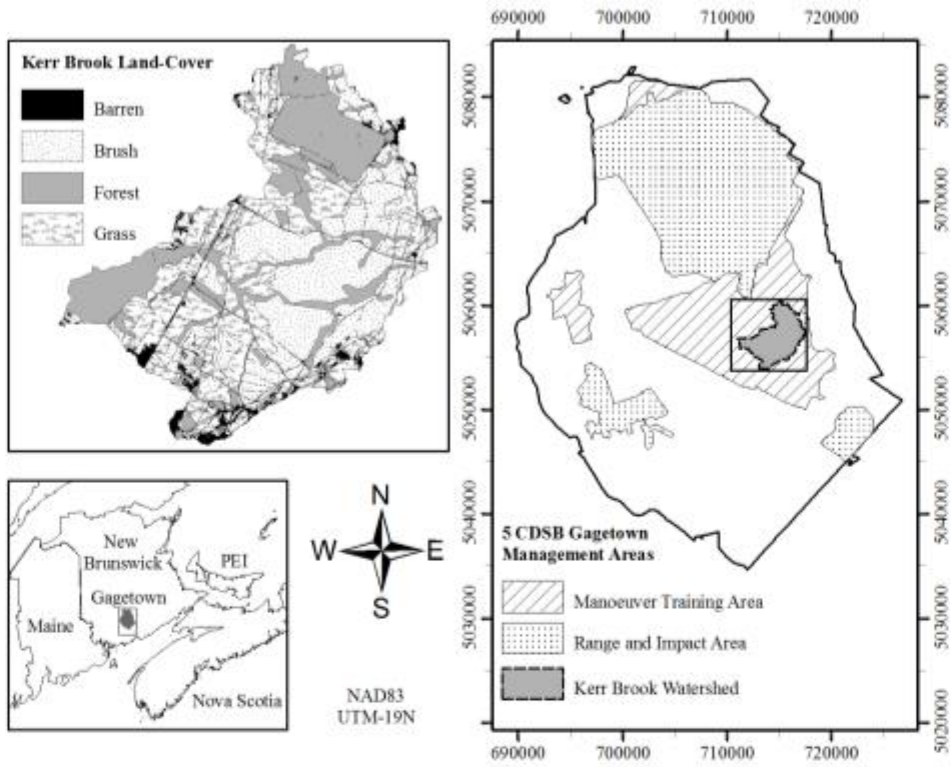


Figure 1|5 CDSB Gagetown and the Kerr Brook watershed.

Annually, the Gagetown training area experiences the equivalent impact of 98,000 personnel training-days, including 800 tracked and 14,000 wheeled vehicle. Military service members generally train throughout the year. However, vehicle operations typically peak in the month of May, which accounts for about 20 % of the annual training load, as tracked by the base Range Control office.

5 CDSB Gagetown is located within the Southern New Brunswick Uplands and Maritime Lowlands. The region receives approximately 885 mm of rainfall a year and 276 cm of snowfall, totaling 1,143 mm of annual precipitation. The daily average temperature is 5.3 ˚C, ranging from -9.8 ˚C in January to 19.3 ˚C in July (Marshall et al. 1999).

Within base boundaries there are 3,272 km of watercourses, 156 lakes and ponds, and 6,487 ha of wetlands. Poor water quality, suspended solids in particular, has been recorded throughout the area (Hood

2013), along with potential stress to some benthic communities (Estrada et al. 2012). Atlantic salmon and brook trout are primary fish species of management interest (Smith 2014).

The Kerr Brook watershed (Figure 1) was selected to test the SWAT model. Centrally located in the base and within the mounted manoeuvre area, this watershed is highly disturbed, regularly used for military training and well documented with meteorological, GIS, hydrometric and water quality data. This 20 km^2 watershed is covered by mixed forests (26 %), grasslands (32 %), brush lands including young pioneer tree species (36 %), and barren features including roads, tracks and highly disturbed manoeuvre areas (4 %). Wetlands, beaver ponds and other water features are evident but cover less than 2 % of the area. Surficial soils are primarily loams and gravelly sandy loams underlain by moderately shallow bedrock. Disturbances that are commonly observed in this area are vehicle ford crossings, dense vehicle rutting across manoeuvre grasslands and persistent barren areas created from repetitive vehicle traffic, demonstrated in Figure 2.

Figure 2|Grasslands, vehicle ruts and barren tracks at 5 CDSB Gagetown.

Methodology

This research approach involved a critical assessment of available information, selection of a suitable numerical tool, followed by model development and application. This initial phase of work provides the framework for subsequent investigation that will focus on expansion of the simulation area, refinement of input parameters, improvements to modelling processes and evaluation of mitigation measures. The scope of this modelling effort excluded winter seasons, detailed vegetation conditions and complex stream channel processes due to data limitations and simulation complexities.

Data Assembly and Analysis

Meteorological data was primarily obtained from a 5 CDSB Gagetown meteorological station located approximately 4 km from the Kerr Brook watershed. A Thiessen polygon analysis indicated that this station provided a reasonable representation of the local climate, with 92 % of Kerr Brook associated to this station. Hourly precipitation, temperature, wind speed and relative humidity data was available. Data gaps were backfilled using adjacent meteorological stations yielding a continuous climate data set from 2007-2012. There were several minor data gaps during winter periods; however, there are negligible flow and water quality observations during these periods. Climate data from 2007 and 2008 was used for the model warm-up period.

GIS data, including a 10 m Digital Elevation Model, surficial soil coverage, and land cover inventories, were provided by the Gagetown Geocell. Surficial soil data were supplemented by various soil survey reports to assist with parameterization of soil conditions (Colpitts et al. 1995; Castonguay and Arp 2002; Fahmy et al. 2010). Land cover information included a land cover inventory, road/track vector data and bare soil raster data classified from Colour Infrared Imagery.

Hourly stream stage data were collected during late spring, summer and fall from 2009-2012 at an upstream and downstream monitoring location in Kerr Brook. Stage-discharge curves were constructed and calibrated to eight discharge measurements throughout this monitoring period.

Simulating erosion, sediment transport and sediment yields are difficult considering the common lack of available sediment data. In order to overcome this limitation, continuous suspended solids information was approximated using a regression approach for comparison to SWAT results (Rasmussen et al. 2011). This multi-linear regression (MLR) model was developed from eight partial storm monitoring events including turbidity, stream flow and Total Suspend Solids (TSS). Other parameters suspected of influencing TSS loading conditions were incorporated into this analysis, including antecedent dry days, cumulative antecedent vehicle activity and rising/falling hydrograph conditions. Variables were selected based on their significance and their ability to significantly improve results. This regression model was applied to an event-flow threshold value, selected from a flow-duration curve. The final model was also applied to all flow conditions and automatically set to a zero TSS load for zero turbidity readings to compare results.

A Water Quality Index (WQI) was computed for the Kerr Brook watershed to assess general water quality conditions. This WQI integrated National Agri-Environmental Standards Initiative-Ideal Performance Standards for TSS and turbidity (Culp et al. 2009), CCME guidelines for pH and water temperature recommendations for brook trout (Birtwell 1999). Average and median daily values were both considered in this analysis. Data were also trimmed with the mirrored 5^{th} percentile to reduce inappropriate deflation of the WQI by low frequency events (Kilgour et al. 2013).

Vehicle water crossing operations have the potential to impair water quality in local streams. Grab samples from ford crossings indicate that this activity can be responsible for turbidity and TSS loadings as high as 1000 NTU and 1000 mg L^{-1}, respectively, immediately downstream of crossing sites. Daily turbidity statistics from the upstream and downstream monitoring locations, including the hourly minimum, 1^{st} quartile, median, 3^{rd} quartile and maximum, were correlated to the daily total vehicle load operating within the Kerr Brook watershed. This analysis was conducted to provide a general indication of whether or not documented vehicle loads impacted observed water quality conditions.

Model Selection

Appropriate model selection is an important aspect of any environmental simulation project.

There are a variety of models which are appropriate for military land, as previously discussed. The new generation of erosion models focuses on highly distributed, physically-based processes which require substantial amounts of input data for small, field-scale applications. While this additional complexity can enhance simulation capabilities, it becomes increasingly cumbersome to apply for large areas and complex models are not always recommended for practical management applications (Grayson et al. 1992). With 5 CDSB Gagetown covering over 1,100 km^2, models that can be effectively applied to large areas are preferable. Available data can be used for calibration and validation of continuous stream flow conditions, giving preference to such models as oppose to event-based or stochastic climate models. SWAT and HSPF are both well supported and commonly applied hydrology-water quality models meeting this criteria. However, HSPF is commonly reported to require substantial parameterization efforts and is not generally considered to be user-friendly (Beckers et al. 2009). Alternatively, SWAT has a relatively straightforward user-interface and is integrated within a simple GIS framework. SWAT was also designed for application in large, ungauged agricultural watersheds requiring minimal parameterization (Neitsch et al. 2011).

SWAT was selected for this study because of its capacity to effectively process and simulate lumped hydrological processes, which can be calibrated and validated with available data. Erosion and overland flow processes are simplified in this model; however, these simplifications make large scale applications efficient.

Model Development

The Kerr Brook watershed was delineated within ArcSWAT with streams defined at a resolution of 66 ha contributing area. Outlets were located at an upstream and downstream monitoring location in addition to two other tributaries. HRUs were defined with a 20 % soil threshold and 20 % slope threshold, resulting in two soil groups and three slope categories. Land cover categories include forest, grass, brush and barren areas. Barren areas were delineated by buffering and merging roads and tracks with bare soils. Other land cover categories were predefined. A 1 % land cover threshold was selected to adequately capture barren areas, which is substantially smaller than the common recommendation of 20 % (Winchell et al. 2007).

Plant growth parameters were adjusted to provide a constant Leaf Area Index; detailed vegetation conditions were unavailable and outside the scope of this study. Water impoundments were neglected in the initial model due to limited land coverage, but integrated in the sensitivity and calibration analysis. Sediment reduction structures, such as grassed waterways and filter strips, were not included due to data limitations.

Sensitivity Analysis and Calibration

A sensitivity analysis and calibration was conducted to improve model parameterization and reduce prediction uncertainty. A combination of manual and automated approaches were used during calibration with both objective and subjective target criteria, as described in Figure 3. From initial parameterization, automated calibration was conducted in the SWAT-CUP interface using GLUE (Abbaspour 2013). GLUE was selected because it was observed to produce more reasonable parameter ranges during trial runs, compared to SUFI2. It was also selected for further analysis because of its simplistic methodology. GLUE established parameter sensitivity and gave the first iteration of an auto-calibrated model. Several iterations were conducted considering different objective function thresholds, downstream and upstream observations or just downstream observations. The initial model was then manually calibrated by targeting annual observed water yields, followed by balancing surface and groundwater ratios. Finally, parameters were calibrated by optimizing the annual Nash-Sutcliffe Efficiency (NSE) and coefficient of determination (R^2) for daily flow conditions. This manually calibrated model was then passed through another iteration of auto-calibration. This procedure is outlined in Figure 3. Sediment yields from the regression model were compared to the simulation results, and not used for calibration of parameters affecting sediment yields.

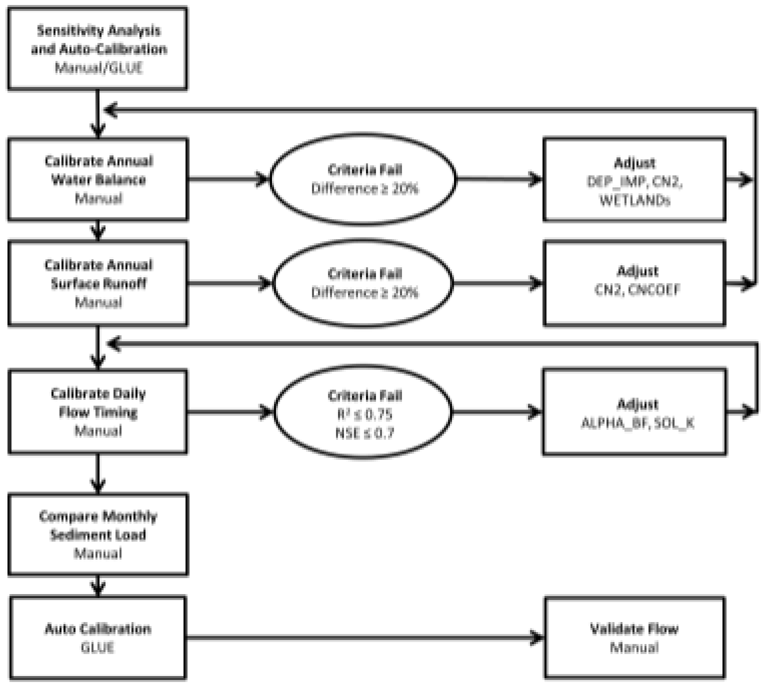


Figure 3|Sensitivity, calibration and validation flowchart.

Parameter identifiability issues affecting groundwater and surface runoff contributions were highlighted during the initial automated sensitivity and calibration analysis. To alleviate this issue, a two-parameter digital filter was used to split stream flow into surface flow and groundwater flow for manual calibration (Eckhardt 2005). Surface erosion is driven by surface runoff making these filter parameters a critical target for calibration. Filter parameters were judged based on literature (Eckhardt 2005), geological conditions and graphical baseflow separation. Two sets of filter parameters were used to assess their effect on parameter calibration. One baseflow filter parameter set was used to disaggregate groundwater into shallow aquifer and hard rock aquifer contributions. Observed flows could then be adjusted to neglect hard rock aquifer contributions, as the SWAT model was expected to inadequately simulate these results due to its single aquifer framework. The other baseflow filter set only predicted shallow aquifer contributions, resulting in both high post-event groundwater flow and extended baseflow.

Results and Discussion

Preliminary Data Analysis

The TSS regression model was developed to consider only turbidity and stream flow. Other variables were discarded based on marginal improvement to the MLR relationship and their insignificance. The threshold confidence level applied for variable consideration was 10 % (α=0.1). Intra-storm event observations were utilized for this analysis due to data limitations (n=41), even though this created concerns about data independence. The finalized regression model is provided below in Equation [1]:

$$TSS = 2.61 + 0.41(T) + 18.00(Q) \qquad [1]$$

In Equation [1], TSS is total suspended solids (mg L^{-1}), T is turbidity (NTU) and Q is discharge ($m^3\ s^{-1}$). The model has a standard error of 41 % and an adjusted R^2 of 0.61. Also, the model and all coefficients are significant except the intercept. This regression model was applied to flows exceeding 0.35 $m^3\ s^{-1}$, corresponding to the 20^{th} percentile exceedance probability where the semi-logarithmic flow-duration curve exhibits a significant change in slope. The model was also applied to all flow conditions for a comparative analysis, which increased annual sediment loads by about 2 %. Results from observed data using this regression model are summarized in Table 1.

Water quality analysis, using the CCME WQI, indicated that water quality in Kerr Brook is marginal; the WQI score ranged from 48-57. This range was established by utilizing combinations of daily median, average and trimmed data for turbidity, modelled TSS, temperature and pH. The addition of more variables is suspected to improve this score as other sources of pollution, such as metals and nutrients, are anticipated to be minimal. There is no deterministic interval established for these calculations; however, conventional applications use discontinuous, daily data collected during relatively steady-state conditions (CCME 2001). The continuous, daily data used in this analysis, and inclusion of storm-event responses, may be deflating these results in comparison to conventional applications.

Table 1. Sediment yield regression results

Observation Year	Observed Months	Sediment Yield (t)	Monthly Max (t)	Monthly Min (t)	Upper 90 % Confidence Yield (t)	Lower 90 % Confidence Yield (t)
2009	4	417	201	24	678	170
2010	7	379	321	0	619	152
2011	7	326	131	0	581	110
2012	5	213	75	0	376	72

Daily vehicle loads within the Kerr Brook watershed were not observed to significantly affect water quality at the watershed outlet; daily turbidity statistics were not strongly correlated to daily vehicle loads. Filtering high flow events and turbidity outliers did not significantly improve this correlation. The only mild correlation was observed for the maximum daily turbidity at the upstream monitoring location (r=0.22). Vehicle load data used in this analysis is insufficient to conclude that vehicle stream crossing activity does not affect watershed water quality. Enhanced monitoring of specific timing and location of stream crossing activity would be required for such a conclusion. However, considering the available data and this analysis, point source sediment contributions from vehicle crossing activities were neglected in modelling efforts.

Modelling Results

The procedure for sensitivity, calibration and uncertainty analysis followed in this study provided an effective means to become familiar with the SWAT model, assess parameter sensitivity, optimize simulation performance and identify problems and limitations of this research approach. Initial sensitivity analysis and auto-calibration achieved reasonably strong statistics for daily flow simulations. Auto-calibration iterations achieved P-factors in the order of 0.83 and R-factors ranging from 0.46-0.53. For these iterations, the NSE ranged from 0.78-0.79 and R^2 ranged from 0.70 to 0.82. However, these results were achieved over a significant parameter range and included a large number of parameters (18). Over 2,000 of the 10,000 simulation runs achieved satisfactory statistics (NSE>0.65). The manner in which this exercise was conducted may have limited its value since a significant number of parameters were included in this analysis over a substantial parameter range. However, this identified the unfortunate issue of equifinality confronted by many models, where many different parameter combinations are able to achieve similar and realistic results (Jetten and Maneta 2011). The flashy nature of this watershed is also suspected to exacerbate the issue of equifinality, with extremely high storm event responses and low baseflow conditions. Parameter sensitivity, identified by t-stat ranking (Abbaspour 2013), also varied between iterations, which may be attributable to the significant degrees of freedom in this initial analysis. Common parameters that were sensitive in different iterations ($P<0.1$) were percolation rates (DEP_IMP), the SCS CN adjustment factor (CNCOEF), groundwater delay (GW_DELAY), soil profile depth (SOL_Z), canopy storage (CANMX), surface runoff lag (SURLAG) and SCS CNs.

This initial sensitivity analysis identified several limitations of this model. Extended baseflow conditions were poorly simulated, likely due to the single aquifer concept in the SWAT model. Flow timing parameters also displayed limited ability to align some event peaks; peak runoff events were occasionally simulated one day in advance of that observed. This is likely due to the daily time-step used in the SWAT model compounded by the flashy nature of the watershed.

The final accepted model from manual calibration achieved a total water yield with a percent difference of approximately 2 % during calibration years. Surface runoff, groundwater flow and deep aquifer recharge contributions were generally predicted within 10 % relative difference of the water balance derived from the baseflow filter analysis. Annual statistics for daily flow simulations were also strong (NSE=0.73-0.79 and R^2=0.86-0.88). Upstream conditions were not as effectively simulated. Water balance components were consistently underestimated and typically ranged between 10-40 %; however, daily flow statistics were still strong (NSE=0.81-0.83 and R^2=0.83-0.84).

Manual calibration identified several key hydrological characteristics. Flatland drainage conditions and selected soil types may be poorly simulated with this model. The upstream drainage area is relatively flat and primarily consists of Tracy Loams. Poor parameterization of these conditions may have resulted in the poor upstream predictions. Wetlands were also introduced in the watershed to mitigate peak flows and reduce total water yields. Wetland parameters were largely estimated; however, surface area and contributing area were approximated from Wet Area Mapping (WAM). Several wetlands were identified by WAM but only one sub-basin wetland significantly improved results. Wetlands were observed in the upstream drainage area but not integrated into the model due to under simulated water yields. Many wetlands in this area are also observed to be influence by beaver ponds, and beaver pond hydrology may be poorly simulated in SWAT.

Meteorological station REM02 was the only station applied to the Kerr Brook model. Adjacent meteorological stations, no more than 15 km away, displayed significant variability in rainfall patterns during selected, intense storms. These storms generally resulted in overestimation of peak flows in the SWAT model. The daily rainfall values for these storms varied up to 75 % or 30 mm between adjacent meteorological stations. Adjusting these rainfall values in the SWAT model proved to be an effective approach to align some of the simulated peak flows. There is potential that the simple meteorological station assignment to Kerr Brook used in this approach does not adequately represent local climate patterns.

Final auto-calibration, utilizing the GLUE program, did not significantly improve results. The number of parameters and parameter ranges were reduced based on knowledge gained during manual calibration. The SCS CN adjustment factor (CNCOEF) and maximum wetland volume (WET_MXVOL) were the only variables that converged to a significant value. Due to limited parameters and parameter ranges, P-factors were very poor (<0.2), emphasizing the requirement to accept exceptional uncertainty for this hydrological model. Manual calibration results were retained due to limited improvement of simulation results from this automated approach.

Simulations during the validation period were not as effective compared to the calibration period. Relative percent different for the total water yield in validation simulations ranged from 2 % in 2009 to 73 % in 2012. Other water balance components, derived from baseflow filtration, ranged from 6-96 %. Annual statistics for daily flow simulations were also poor (NSE=-0.46-0.47 and R^2=0.5-0.64). Upstream simulations were more agreeable, with simulated water yields ranging from 12-34 % and water balance components ranging from 2-66 %. Annual statistics for upstream daily flow simulations were better than downstream simulations, but still generally poor (NSE=0.47-0.54 and R^2=0.5-0.62). Simulated and observed daily downstream discharge values are displayed in Figure 4. Land cover SCS CNs for these results were 70, 82, 76 and 86 for forests, grasslands, brush and barren areas, respectively. The average annual precipitation of 1170 mm saw 57 % contribute to ET, 18 % to surface runoff, 14 % to shallow groundwater flow and 8 % to deep groundwater flow. Alternative baseflow filter parameters could see these annual groundwater and surface runoff contributions shifting in the order of 30-90 %.

The model consistently overestimated fall stream flow in 2012. The first storm in the fall of 2012 saw the largest daily rainfall event in the simulated time period of 118 mm. It is suspected that this error may be attributed to a disturbance that this storm event caused to the stream channel or data level logger, disrupting the stage-discharge relationship of the monitoring site. However, this error may also be attributable to a poorly simulated storage component in the SWAT model, such as soil, surface or wetland storage, but this is less likely.

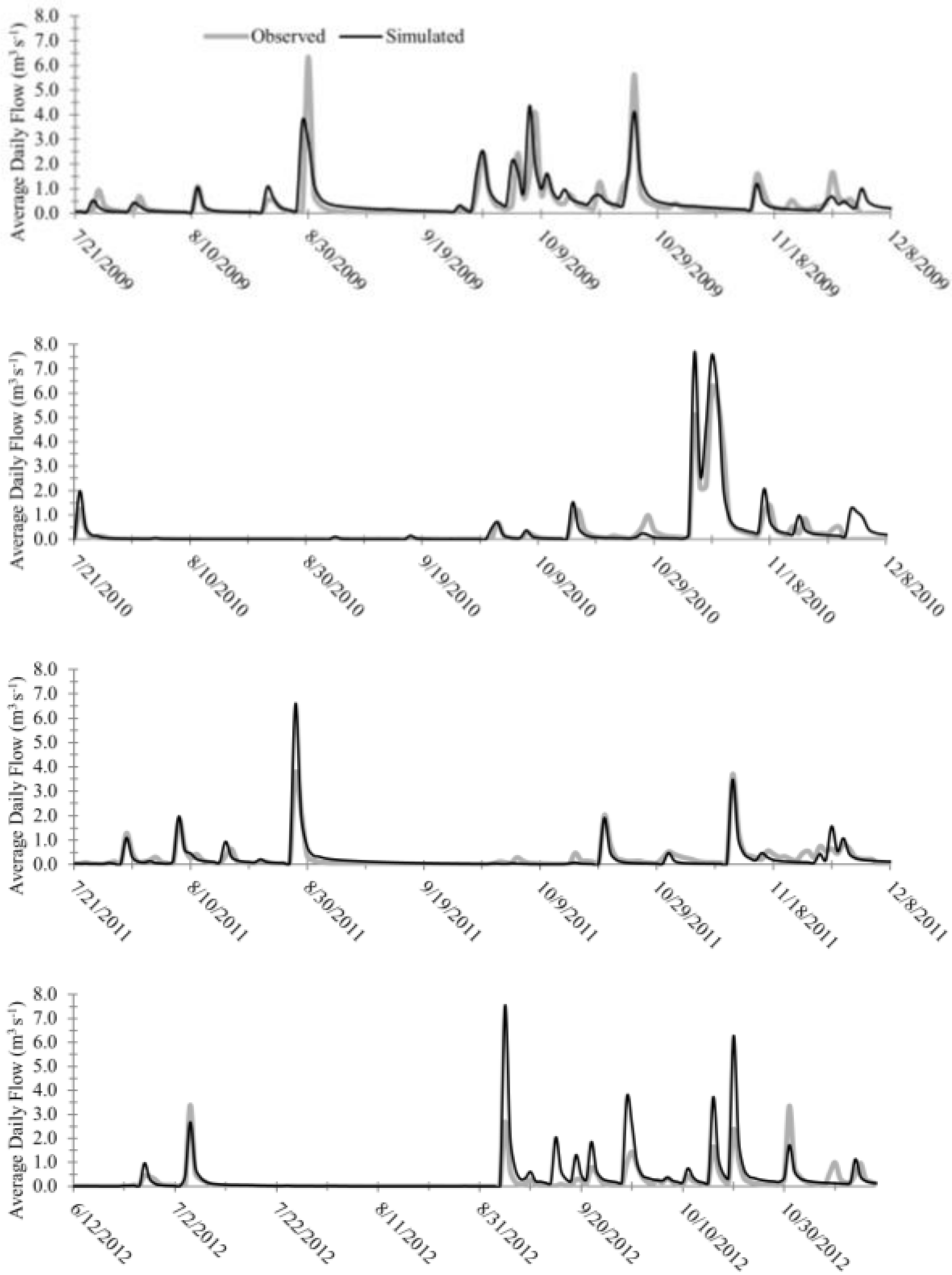


Figure 4|Simulated and observed downstream discharge.

Annual downstream sediment yields were generally adequate compared to the regression model from 2009-2011 (%d=6-47 %). 2012 sediment yield were overestimated by 217 % primarily due to poorly simulated and/or observed flow conditions. Monthly sediment yields from the SWAT model and regression model are displayed in Figure 5. Simulated annual average sediment yields were in the order of 700 t yr^{-1}. This annual yield can be compared to the Black Brook watershed in New Brunswick, which is 14.5 km^2 covered by 10 % urban areas, 25 % forests and the remainder agricultural crops. The observed annual sediment yields for this watershed have ranged from 1,526-8,092 t yr^{-1}, with 39 % of the load generally occurring during the April snow-melt period (Yang et al. 2011). Simulated erosion rates ranged up to 6 t ha^{-1} and 11 t ha^{-1} for grasslands and barren areas, respectively. This corresponds to a low erosion class; however, most simulated HRU erosion rates were less than 6 t ha^{-1}, which fall into the lowest, tolerable erosion class (Wall et al. 2002). Many sediment reduction processes are not simulated in this model, due to model and data limitations. Erosion rates are likely underestimated in the SWAT model; however, surface and aquatic deposition rates are also likely underestimated.

Simulated upstream sediment yields were consistently overestimated compared to those estimated from the regression model (%d=76-384 %).This error is suspected to be attributable to the flat topography of the upstream drainage area, which would impact sediment transport and deposition patterns across the landscape. Low order streams are also thoroughly buffered with forested areas in the upstream sub-basin, raising conceptual model issues with filter strip definition and inter-HRU interactions. Wetlands and beaver ponds may also be attributable to low sediment yields. However, wetlands were not integrated into the upstream drainage area because water yields and peak flow were generally underestimated, and wetland integration would only exacerbate this issue. Land cover area ratios between the upstream and downstream contributing areas are relatively the same, so cover characteristics were not suspected to be the source of this error.

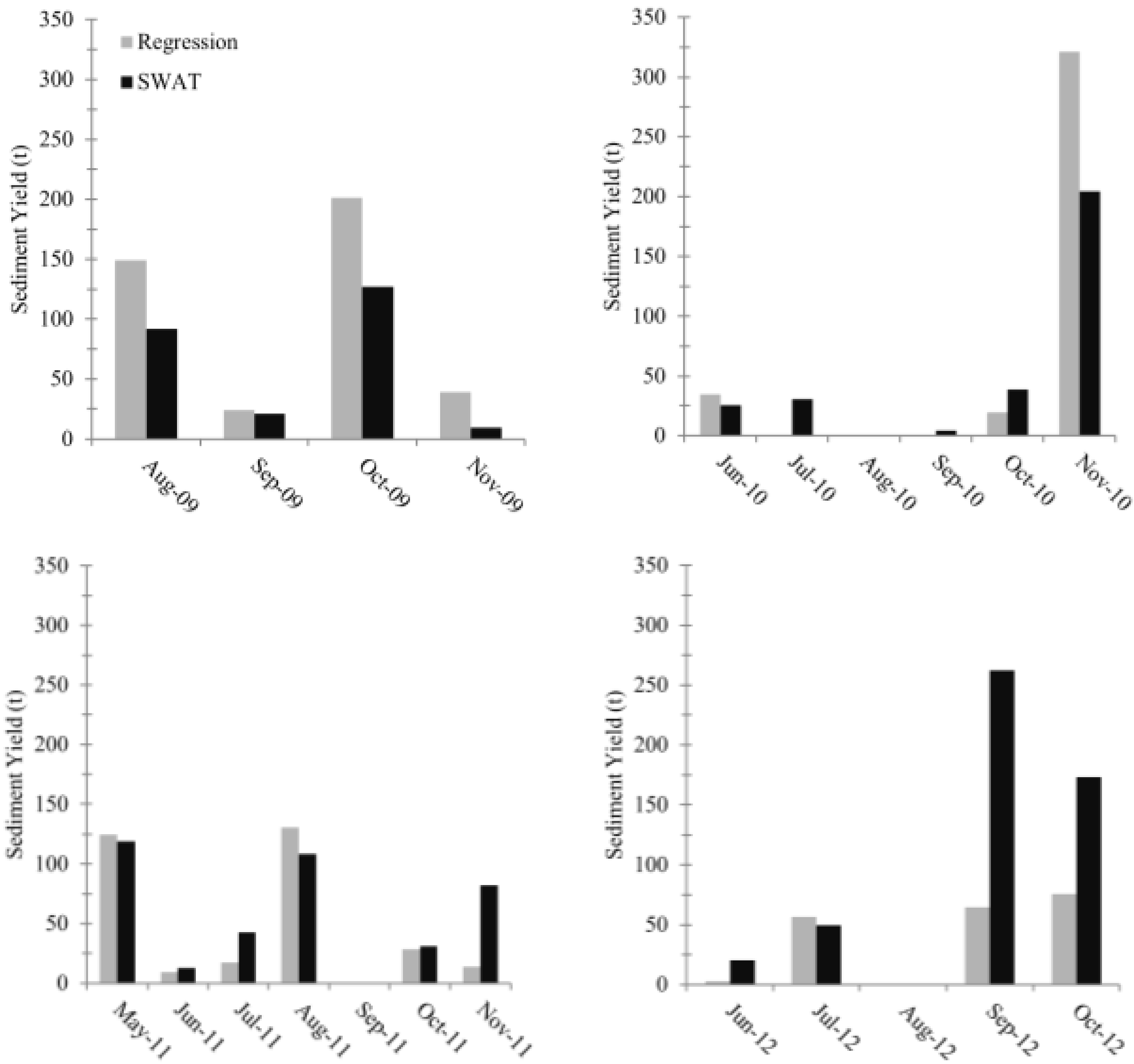


Figure 5|SWAT and regression model monthly downstream sediment yield.

High runoff baseflow filter parameters achieved better sediment results than low runoff filter parameters. Also, adjusting parameters, such as slope length, cover-factors, and filter strip, were capable of significantly affecting total sediment yields. Considering the uncertainty associated with runoff quantity and these other sediment parameters, there would be a considerable number of parameter sets able to achieve reasonable sediment yield results. Improved characterization of surface runoff quantity, cover-factors and sediment reduction parameters would greatly increase confidence in model results. The final results reported for this model did not include filter parameters, slope adjustments or cover adjustments because a proper calibration exercise would not consider TSS regression model results as a valid calibration target.

Conclusion and Recommendations

The Kerr Brook SWAT model effectively simulated stream flow conditions for three out of four years of observation. Sediment yields during these three years were generally agreeable with TSS regression model results. The best simulation predicted acceptable total water yields, excellent daily flow conditions and acceptable monthly sediment loads. This is not to say the model confidently simulated the natural hydrological and sediment cycle within Kerr Brook. Uncertainties associated with surface runoff and baseflow ratios, soil storage, wetland storage and deep aquifer loss may be significant. Many parameter combinations were capable of achieving satisfactory statistics during automated approaches. Subjective baseflow filtration, along with manual calibration, was the most effective means to achieve a unique solution in this application.

Further advancements in this research are recommended as follows:

- The SWAT model could be expanded to include a larger area at 5 CDSB Gagetown for immediate, practical application. This should include a time-series extension which would preferably capture well documented land cover changes;
- An expanded data collection effort could be implemented to facilitate parameter refinement to improvement confidence in the model. This effort could include tracer tests for baseflow separation (Klaus and McDonnell 2013) and sediment fingerprinting (Mukundan et al. 2012) to provide additional insight into watershed hydrology and sedimentation processes;
- Continued monitoring of event-based turbidity, flow and TSS could be used to improve the TSS regression analysis. This would enable the implementation of daily observed values or daily regression results to increase the accuracy of sediment observations for model calibration and validation;

- Remote sensing techniques, supported by field survey quality control data, could be applied to refine plant and cover parameters, improved characterization of wetlands and parameterize surface features, such as filter strips;
- Lastly, enhancements in numerical simulations could enhance this field of study. This could see the application of more distributed, process-based models, such as WEPP or LISEM. Improvements to the SWAT model could also be conducted, such as the addition of multiple groundwater reservoirs or consideration of variable source areas (Easton et al. 2008). Other natural processes could also be studied, modelled and integrated into a watershed level context. This could include detailed consideration of road erosion or channel erosion processes.

This work has demonstrated that the SWAT model is a capable tool for simulating large-scale hydrological and erosion processes. With continued research, hydrological and water quality impacts from select military activities and landscape alterations may be assessed with this model. Management practices, such as mulching, wetland construction and tillage operations, also have the potential to be simulated in this model in order to guide land management decisions. Land managers at 5 CDSB Gagetown have limited, quantitative understanding of watershed processes and how they are affected by the diverse and unique conditions of military training grounds. The scale of this area and the ability to affect significant change across the landscape instil significant cause to objectively manage detrimental impacts to the hydrological and sediment cycle. SWAT holds potential to guide the design of landscape alterations and mitigation efforts, and with continued research, could be an effective tool for this application.

Acknowledgements

Many organizations provided critical data and support for this study. The Department of Fisheries and Oceans collected most hydrometric and water quality data used in this research, including stage-discharge analysis. The Meteorological and Geocell Sections at 5 CDSB Gagetown provided most climate and GIS data, respectively. The Royal Military College Environmental Science Group and Environmental Services Branch at 5 CDSB Gagetown also provided valuable support and guidance throughout this study. The efforts of all those involved is greatly appreciated.

References

Abbaspour KC. 2013. SWAT-CUP: Calibration uncertainty program. Swiss Federal Institute of Aquatic Science and Technology, EAWAG.

Beckers J, Smerdon B, Wilson M. 2009. Review of hydrologic models for forest management and climate change application in British Columbia and Alberta. FORREX, Forum for Research and Extension in Natural Resources, Kamloops, British Columbia.

Birtwell IK. 1999. The effects of sediment on fish and their habitat. Canadian Stock Assessment Secretariat Research Document, 99/139.

Canadian Council of Ministers of the Environment. 2001. CCME water quality index: user's manual. *In* Canadian Environmental Quality Guidelines, 2001. Canadian Council of Ministers of the Environment, Winnipeg, Manitoba.

Castonguay MA, Arp PA. 2002. Physical and chemical properties of soil around four of eight meteorological stations at CFB Gagetown, New Brunswick. Faculty of Forestry and Environmental Management, University of New Brunswick, Fredericton.

Colpitts MC, Fahmy SH, MacDougall JE, Ng TM, McInnis BG, Zelazny VF. 1995. Forest soils of New Brunswick. Agriculture and Agri-Food Canada, Research Branch, Contribution No. 95-38.

Culp JM, Benoy GA, Brua RB, Sutherland AB, Chambers PA. 2009. Total suspended sediment, turbidity and deposited sediment standards to prevent excessive sediment effects in Canadian streams. National Agri-Environmental Standards Initiative Synthesis Report No. 13. Environment Canada, Gatineau, Quebec.

Dalton JC. 2008. Erosion assessments: training load optimization for environmental and economic considerations. United Stated Army Corps of Engineers, Public Works Technical Bulletin 200-3-56.

Deinlein R., Bhöm A. 2000. Modelling overland flow and soil erosion for a military training area in southern germany. *In* Schmidt J (ed.), 2000. Soil erosion: application of physically based models. Springer, Berlin, Heidelberg, New York.

Donigian AS, Imhoff J, Mishra A, Deliman P, Regan E. 2010. A watershed modelling framework for military installations: assessment of the hydrologic and sediment washoff impacts of military management alternatives. Proceedings of the 2nd Joint Federal Interagency Conference, Las Vegas, Nevada.

Easton ZM, Fuka DR, Walter MT, Cowan DM, Schneiderman EM, Steenhuis TS. 2008. Re-conceptualizing the soil and water assessment tool model to predict runoff from variable source areas. J. Hydrol. **348:**279-291.

Eckhardt K. 2005. How to construct a recursive digital filter for baseflow separation. Hydrological Processes **19:**507-515.

Estrada E, Laing T, Paquin V, Fortin P, Rance S. 2012. Benthic invertebrate monitoring program for CFB Gagetown: 2011 results and multi-year data analysis. Technical report, Environment Science Group, Kingston.

Fahmy SH, Hann SWR, Jiao Y. 2010. Soils of New Brunswick: the second approximation. Agriculture and Agri-Food Canada, Eastern Canada Soil and Water Conservation Centre, Publication No. NBSWCC-PRC 2010-01.

Flanagan DC, Frankenberger JR, Cochrane TA, Renschler CS, Elliot WJ. 2013. Geospatial application of the water erosion prediction project model. American Society of Agriculture and Biological Engineers **56:**591-601.

Gaffer RL, Flanagan DC, Denight ML, Engel BA. 2008. Geographic information system erosion assessment at a military training site. J. Soil Water Conserv. **63:** p. 1-10.

Grayson RB, McMahon TA, Moore ID. 1992. Physically based hydrologic modelling: is the concept realistic. Water Resour. Res., **28:**2659-2666.

Hood D. 2013. Draft surface water quality monitoring: CFB Gagetown range and training area 1997-2012. Synoptic Data Report, Department of Fisheries and Oceans Canada, Ecosystem Management.

Jager HI, Bevelhimer MS, King RL, Smith KA. 2011. Landscape influences on headwater streams on fort stewart, Georgia, USA. Environ. Manage **48:**795-807.

Jetten VG, Maneta MP. 2011. Calibration of Erosion Models. *In* Morgan RPC, Nearing MA (eds.), Handbook of Erosion Modelling. Wiley-Blackwell, West Sussex.

Kilgour BW, Francis AP, Mercier V. 2013. Reducing the sensitivity of the water quality index to episodic events. Water Qual. Res. J. Can. 48: 1-13.

Klaus J, McDonnell JJ. 2013. Hydrograph separation using stable isotopes: review and evaluation. J. Hydrol. **505:**47-64.

Koch DJ, Ayers PD, Howard HR, Siebert G. 2012. Vehicle dynamics monitoring and tracking system. United States Army Corps of Engineers, Construction Engineering Research Laboratory.

Liu J, Liu S, Tieszen LL, Chen M. 2007. Estimating soil erosion using the USPED model and consecutive remotely sensed land cover observations. Proceedings of the 2007 Summer Computer Simulation Conference.

Luce CH, Black TA. 2001. Spatial and temporal patterns in erosion from forest roads, p. 165-178. Wigmosta MS, Burges SJ (eds.) In Influence of Urban and Forest Land Uses on the Hydrologic-Geomorphic Responses of Watersheds. Water Resources Monographs, American Geophysical Union, Washington, DC.

Marshall IB, Schut PH, Ballard M. 1999. A national ecological framework for Canada: attribute data. Agriculture and Agri-Food Canada, Research Branch and Environment Canada, State of the Environment Directorate. Available on-line at: http://sis.agr.gc.ca/cansis/nsdb/ecostrat/1999report/data_tables.html. [Modified: 27 May 2013; accessed 1 June 2013].

Mukundan R, Walling DE, Gellis AC, Slattery MC, Radcliffe DE. 2012. Sediment source fingerprinting: transforming from a research tool to a management tool. Journal of the American Water Resources Association **48:**1241-1257.

Neitsch SL, Arnold JG, Kiniry JR, Williams JR. 2011. Soil and water assessment tool theoretical documentation. Texas A&M University System, Texas Water Resources Institute Technical Report, No. 406.

Rasmussen PP, Gray JR, Glysson GD, Ziegler AC. 2011. Guidelines and procedures for computing time-series suspended-sediment concentrations and loads from in-stream turbidity-sensor and streamflow data. United States Geological Survey Techniques and Methods, 3-C4.

Roo APJ, Wesseling CG, Jetten VG, Ritsema CJ. 1996. LISEM: a physically-based hydrological and soil erosion model incorporated in a GIS. Application of Geographic Information Systems in Hydrology and Water Resource Management, Proceedings of the Vienna Conference, no. 235.

Smith A. 2014. Strategies for the management of fisheries and aquatic habitat at 5th Canadian Division Support Base Gagetown: draft. 5th Canadian Division Support Group, Environmental Service Branch, Oromocto, New Brunswick.

Stanley B, Arp P. 2002. Effects of forest harvesting basin-wide water yield in relation of % of watershed cut: a review of literature. University of New Brunswick, Faculty of Forestry and Environmental Management, Fredericton, New Brunswick.

Steichen JM, Hutchinson SL, Zhang N, Hutchinson JMS, Oviatt CJ, Anderson A, Keane T, Barnes PL. 2008. Assessing the impact of maneuver training on NPS pollution and water quality. Strategic Environmental Research and Development Program, project SI-1339.

Stevens MR, Dupree JA, Kuzmiak JM. 2008. Temporal and spatial variations in precipitation, streamflow, suspended-sediment loads and yields, and land-condition trend analysis at the U.S. Army Piñon Canyon maneuver site, Las Animas County, Colorado, 1983 through 2007. USGS Scientific Investigations Report 2008–5111, U.S. Geological Survey, Reston, Virginia.

Vega-Nieva DJ, Murphy PNC, Castonguay M, Ogilvie J, Arp P. 2008. A modular terrain model for daily variations in machine-specific forest soil trafficability. Can. J. Soil Sci. **89:**93-109.

Wall GJ, Coote DR, Pringle EA, Shelton IJ. 2002. Revised universal soil loss equation for application in Canada: a handbook for estimating soil loss from water erosion in Canada. Agriculture and Agri-Food Canada, Research Branch, Ottawa, Contribution No. AAFC/AAC2244E.

Warren SD, Diersing VE, Thompson PJ, Goran WG. 1989. An erosion-based land classification system for military installations. Environ. Manage **13:**251-257.

Warren SD, Mitasova H, Hohmann MG, Landsberger S, Iskander FY, Ruzycki TS, Senseman GM. 2005. Validation of a 3-D enhancement of the universal soil loss equation for prediction of soil erosion and sediment deposition. Catena **64:**281-296.

Wigmosta M, Lane L, Coleman A, Tagestad J, Roberts D. 2007. Development of an adaptive framework for management of military operations in arid/semi-arid regions to minimize watershed and in-stream impacts for non-point pollution. Strategic Environmental Research and Development Program, project SI-1340.

Winchell M, Srinivasan R, Di Luzio M, Arnold J. 2007. ArcSWAT interface for SWAT2005: user's guide. Blackland Research Center & Grassland, Soil and Water Research Service.

Winter TC, Harvey JW, Franke OL, Alley WM. 1998. Groundwater and surface water as a single resource. United States Geological Survey, Denver, Colorado, Circular 1139.

Yang Q, Benoy GA, Zhao Z, Chow TL, Bourque CPA, Meng FR. 2011. Watershed-level analysis of exceedance frequencies for different management strategies. Water Qual. Res. J. Can., **46:**64-73.