Assessment of the effective width of riparian buffer strips to reduce suspended sediment in an agricultural landscape using ANFIS and SWAT models

Zacharie Sirabahenda[a], André St-Hilaire[a,*], Simon C. Courtenay[b], Michael R. van den Heuvel[c]

a. Canadian Rivers Institute, INRS-ETE, 490 Rue de la Couronne, Québec City (QC), G1K 9A9, Canada.
b. Canadian Rivers Institute, University of Waterloo, School of Environment, Resources and Sustainability, 200 University Avenue West, Waterloo (ON), N2L 3G1, Canada.
c. Canadian Rivers Institute, University of Prince Edward Island , Department of Biology, 550 University Avenue, Charlottetown (PEI), C1A 4P3, Canada.

* Corresponding author.

INRS-ETE

490 rue de la Couronne

Quebec City (QC)
Canada, G1K 9A9
E-mail address: andre.st-hilaire@ete.inrs.ca

Abstract

Riparian buffers are important features that help to mitigate suspended sediment loads within rivers running through agricultural landscapes. Evaluating their effectiveness for sediment control by different modelling approaches can help direct beneficial management practices. The Soil and Water Assessment Tool (SWAT) model and the Adapted Neuro-Fuzzy Inference System (ANFIS) based model were used for prediction of suspended sediment concentrations (SSC) and sediment loads in the Mill River watershed (PEI, Canada). Those models were then used to assess the impact of riparian buffer widths in reducing sediment loads. The ANFIS model predicted measured SSC more accurately than the SWAT model. The relationship between buffer width and sediment reduction was asymptotic, and the relationship begins to plateau when the width reaches 50 m. Increasing the buffer width from 15 to 100 m led to an increase in sediment loads retention of 30.5% and 36.2% of the total stream sediment load for the SWAT and ANFIS models, respectively. This study highlighted that a data-driven ANFIS based model can be used to simulate the impact of land use changes on the sediment delivery in a river.

Key words: Agriculture, Riparian buffers, Sediment yield, SWAT model, ANFIS model.

1. Introduction

Agriculture is reported by the United States Environmental Protection Agency as the most widespread cause of stream pollution (U.S. Environmental Protection Agency, 2000). Sediment, bacteria and nutrients constitute the three leading sources of water pollution from agriculture (Liu *et al.*, 2008; Beaudry, 2017; FAO & IWMI, 2017), often resulting from environmental land use conflicts (Pacheco et al., 2014). In addition, soil particles being transported in surface waters can be contaminated by adsorbed heavy metals or organic pollutants (Kadokami *et al.*, 2013; Song *et al.*, 2017) and affect both aquatic flora and fauna (Beyer *et al.*, 2014). The turbidity of river water increases as a function of the increase of sediment loads with negative consequences on fish habitat, the growth of aquatic plants and invertebrate species (Ramskov *et al.*, 2015; Valero *et al.*, 2017).

Watersheds without sustainable land use and soil management practices are subjected to increased erosion with high rates of soil loss (Shi *et al.*, 2017; Mello *et al.*, 2018; Schmidt *et al.*, 2018). The increase of soil erosion in agricultural areas is related to the precipitation regime, land slope, soil properties and farming management and practices (Montgomery, 2007; Keesstra *et al.*, 2016; Restrepo & Escobar, 2018). Riparian buffer strips are multifunctional management tools that play an important role for river water quality and are vital for aquatic biodiversity and riparian habitat (Mankin *et al.*, 2007; McCracken *et al.*, 2012; Stutter *et al.*, 2012). Implementing riparian buffer zones is the most natural mitigation measure allowing for surface runoff reduction, pollutants filtering and sediment retention while additionally creating corridors of riparian habitat along streams and regulating stream temperature. The optimal width of riparian buffer strips can vary depending on the intended function (e.g., retention of sediment vs. nutrients Hawes & Smith, 2005; Chang *et al.*, 2011; Shan *et al.*, 2014; Miller *et al.*, 2015) and on landscape configurations (Tim et al., 1995). Understanding of the impact of buffer strips for sediment control in agricultural landscape is crucial to evaluating their effectiveness (Sahu & R. Gu, 2009; Betrie *et al.*, 2011; Monteiro *et al.*, 2016; Vigiak *et al.*, 2016; Mello *et al.*, 2017).

Hydrological and erosion/sediment models, in combination with monitoring, are essential tools to assist watershed managers in implementation of strategies and policies for water quality preservation, particularly for the optimisation of the beneficial management practices for achieving water quality targets (Hould-Gosselin *et al.*, 2016; van Vliet *et al.*, 2016; Romano *et al.*, 2018). Physical processes related to erosion and sediment transport are modelled with empirical or/and semi-deterministic approaches and this results in two main types of models, namely data-driven models and physical process-based models. Data-driven models and physical process-based models have different strengths and limitations for estimating suspended sediment concentrations (SSC) and sediment loads. Despite their relatively easy implementation for examining impacts of changes in landscape management practices, physical process-based models can require a large number of inputs, adjustment of numerous parameters and high computational time during calibration, compared to data-driven models (Hamaamin *et al.*, 2016). However, the potential of data-driven models for exploring the implications of altering factors that may influence erosion, such as land-use/land-cover in agricultural watersheds, remains relatively unexplored.

Prince Edward Island (PEI, Canada) is a highly agricultural province and increasing degradation of the environmental conditions of its streams, estuaries and coastal waters is recognized (Coffin *et al.*, 2018). Sediment deposition and suspension in rivers resulting from intense agricultural activities have been well documented in the region (Alberto *et al.*, 2016; Sirabahenda *et al.*, 2017). Monitoring of suspended sediment during 2013 - 2017 showed that the sediment loads are high in several PEI Rivers and stakeholders involved in watershed management have to consider mitigating actions in order to attenuate erosion (Sirabahenda *et al.*, 2017). One cost-effective strategy to guide mitigations consists of implementing robust decision-making tools.

The objective of this study was to compare the effectiveness of a semi-deterministic model and an empirical model for prediction of SSC and sediment loads in an agricultural watershed. Secondly, those models are used to develop a methodology to calculate effective riparian buffer widths to reduce sediment loads. To this end, a lumped nonparametric model, the Artificial Neuro-Fuzzy Interface System (ANFIS; Jang, 1993) based model, including a new parameter related to soil and land-use characteristics, was developed by Sirabahenda *et al.* (2017). This model is used along with the well-known semi-deterministic model, the Soil and Water Assessment Tool (SWAT) model with the goal of simulation of impacts from different scenarios of land use and management on sediment loads using a PEI watershed.

2 Materials and Methods

2.1 Study site and data gathering

The Mill River is located in Prince Edward Island, Canada and flows into the southern Gulf of St Lawrence (Figure 2). The Mill watershed covers an area of 120.4 km^2 and the drainage upstream of the sediment monitoring station (46°44'39.6"N, 64°11'2.1"W) is 46.2 km^2. Total annual precipitation in the region is 1081 mm (Summerside meteorological station), with the months of December to March receiving snow. Drainage basin elevations vary between 0 and 60 m ABSL. The steeper slopes are located near the river banks and slopes are classified such that 59.3% and 12.7% of watershed area are under 1% and above 3%, respectively. The principal soil types of the Mill watershed and their drainage classes are presented in Table 1 (Research Branch Agriculture Canada/PEI Department of Agriculture, 1994). The geological formation of the native rocks of those sedimentary soils is considered to be Triassic Age with dominant feature of red color (van der Poll, 1983). The three main types of land use/land cover for the studied watershed (Figure 2) were agriculture (31.3%), forest (60.7%) and wetlands (6.4%).

Table 1. Distribution area (%) of soil series for Mill Watershed.

Drainage class	Soil types names
Well drained	Charlottetown (7.5%)
Moderately drained	Margate (39.9%), Tignish (7.2%), O Leary (24.2%); Albery (3.0%)
Poorly drained	Duvar (14.5%)

Suspended sediment data were monitored in the Mill River using turbidity from May 15, 2013 through September 30, 2017. An YSI (Yellow Springs Instrument) turbidity probe that measures reflectance of infrared radiation by the suspended sediments and translates it into Nephelometric Turbidity Units (NTU), was deployed. The sampling frequency was 30 min with an automatic cleaning after 24 h and a seasonal recalibration of the probe. The relation between the turbidity and SSC was determined by establishing a calibration curve with grab samples of river sediments with varying dilution to cover the range of measured turbidity. Each grab sample was subsequently filtered, dried and weighed to determine SSC. The detailed description is given by Sirabahenda *et al.* (2017) for calculation of the non-linear mathematical relationship between SSC and turbidity for the Mill River. Meteorological data, including precipitation, temperature, wind speed, solar radiation and humidity were obtained from local weather stations (Alberton Snow, Tyne Valley, Harrington CDA CS and Summerside stations) operated by Environment and Climate Change Canada (http://climate.weather.gc.ca). Streamflow data were obtained from Environment and Climate Change Canada (Water Survey Division) for Carruthers Brook near St-Anthony station (http://wateroffice.ec.gc.ca).

Please include Figure 1 here.

2.2 SWAT model description and set up

The SWAT model (Arnold et al., 2012; https://swat.tamu.edu) is a physical process-based model that enables simulation of the impacts of land use practices on waterbodies (qualitatively and quantitatively) at the watershed scale (Neitsch *et al.*, 2011). For spatial discretization, the watershed is partitioned into sub-watersheds, which are further divided into Hydrologic Response Units (HRUs) comprised of unique combinations of land cover, slope and soil type.

Processes modeled by SWAT include canopy storage, snow melt, surface runoff and infiltration, crop growth, evapotranspiration, erosion and transport of sediments, nutrients and pesticides. Erosion generated by precipitation and surface runoff is calculated using the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1995). The MUSLE is a function of runoff factors (peak and volume of runoff), soil erodibility factor, cover and management factor, support practice factor, a topographic factor and a coarse fragment factor. A detailed description of the physical processes involved in modelling the hydrological cycle and related to the loadings of sediments, nutrients and others pollutants and their movement through the channel network is presented by Neitsch *et al.* (2011) in the SWAT theoretical documentation (http://swatmodel.tamu.edu).

In this study, an ArcGIS-ArcView extension and graphical interface for SWAT, ArcSWAT 2012 was used to set up the model by using watershed characteristics obtained from a database including Digital Elevation Model (DEM), soil, land use and climatic data. GIS data layers for the stream network and 2 m contour lines (PEI Department of Environment/ Energy & Forestry and Resource Inventory, 2010) were used for the DEM construction and further sub-classification of areas in the Mill watershed. The Mill watershed was delineated into 25 sub-basins, from a reduced resolution DEM of 10 m, which were then further partitioned into Hydrologic Response Units (HRUs). The distribution of HRU within the Mill watershed was set up using multiple HRUs per sub-basin option with the same minimum areal coverage threshold of 5% for land use, soil and slope classes to be considered. Then, subdividing the sub-basin into homogeneous areas having unique soil, land use and management combinations resulted in a total of 479 HRUs for the Mill watershed. The largest sub-basin has an area of 587.3 ha while the smallest sub-basin has an area of 5.4 ha. Some statistics regarding the area of those HRUs from the sub-watersheds are shown in the Table 2.

Table 2 Statistics for area of the HRUs

Statistic for the HRUs from the sub-watersheds						
Interval area [ha]	Sum area [ha]	Number of HRUs	Max [%]	Mean [%]	Min [%]	Sd [%]
1-10	1020.97	366	24.31	2.32	0.03	2.99
10-40	1626.02	87	39.19	10.54	2.08	7.52
40-80	895.13	18	51.07	26.39	7.84	14.75

80-200	1076.81	8	58.84	32.23	17.19	13.41

For overland flow, the modified Soil Conservation Service (SCS) curve number method (USDA Soil Conservation Service, 1972) was selected to estimate the amount of runoff. The modified rational method (Kuichling, 1889) was used to calculate runoff peaks and the potential evapotranspiration was computed using Monteith (1965). The variable storage routing method (Williams, 1969) was chosen to route water through the channel flow network to the watershed outlet. The SWAT model estimated sediment erosion due to precipitation and runoff using the MUSLE and the simplified version of Bagnold (1977) stream power equation was chosen for sediment routing, including sediment resuspension and deposition phenomena.

The calibration was performed manually (Neitsch *et al.*, 2002) using daily time steps by iteratively adjusting the parameters and comparing simulated results to observations for streamflow and sediment loads. The baseflow filter program (Arnold *et al.*, 1995; Arnold & Allen, 1999) available on https://swat.tamu.edu was used for partitioning observed stream flow into base flow and surface runoff. For the hydrological model component, the surface runoff was firstly calibrated by adjusting the parameters such as the curve number (CN2), soil available water capacity (SOL_AWC) and soil evaporation compensation factor (ESCO). Secondly, the base flow was calibrated considering the following parameters: the groundwater "revap" coefficient (GW_REVAP), the threshold depth of water in the shallow aquifer for "revap" to occur (REVAPMN) and the threshold depth of water in the shallow aquifer required for base flow to occur (GWQMN). Finally, the parameters that impact the shape of the hydrograph such as the channel hydraulic conductivity coefficient (CH_K) for the transmission losses, the roughness coefficient (OV_N), the base flow alpha factor (ALPHA_BF), the temperature lapse rate (TLAPS) and minimum/maximum melt rates (SMFMX and SMFMN) for snow melt, were adjusted until values were acceptable for both water balance and stream flow. For the sediment model component, the following parameters were adjusted for sub-watershed sediment loads in addition to runoff factors calculated during the hydrologic calibration process: crop management factor (USLE_P), crop practice factor (USLE_C), crop residue coefficient (RSDCO) and bio-mixing efficiency (BIOMIX). The slope length factor (SLSUBBSN) and the slope of HRUs (SLOPE) were adjusted to represent realistic values of the watershed and HRUs. For channel routing, the parameters related to sediment degradation and deposition processes such as the channel cover and erodibility factors (CH_COV and CH_EROD), linear and exponential coefficient for sediment re-entrainment in channel (SPCON and SPEXP), were also adjusted during sediment calibration.

The hydrological module calibration was performed for the period of January 2007 through December 2015, while the data from January 2000 through December 2003 were used to validate the hydrological component of the SWAT model. The period 2007-2015 was selected for calibration because it encompassed greater variability than 2000-2003 (larger number of high values). Also, the period from January 2004 through December 2006 was fixed as the model spin up period for SWAT simulations. Sediment module calibration and validation were done using data from May 2013 through December 2015, and from January 2016 through September 2017 respectively. The performance of the model was evaluated through graphical analysis between simulated and measured data and calculation of three statistical metrics (Table 3) recommended by (Moriasi *et al.*, 2007): the Nash-Sutcliffe efficiency (NSE), the root mean square error-observations standard deviation ratio (RSR) and the percent bias (PBIAS). The Nash-Sutcliffe Efficiency (Nash & Sutcliffe, 1970) is a standardized measure that determines the relative magnitude of the residual variance compared to the measured data variance. The PBIAS quantifies the average tendency of the simulated data to be larger or smaller than the observed data (Gupta *et al.*, 1999). The RSR is a measure of the ratio of the Root Mean Square Error (RMSE) and the standard deviation of the observed data.

Table 3. Performance rating and statistical criteria. $\boldsymbol{X_i}$ and $\boldsymbol{\bar{X}_i}$ refer to the observed data and their average respectively, $\boldsymbol{Y_i}$ refer to the simulated data and *n* is the number of observations.

Performance criteria	**Performance Rating** : Good (Moriasi et al., 2007; Monthly time steps)	
Equations	**Streamflow**	**Sediment**
$\boldsymbol{NSE = 1 - \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}(X_i - \bar{X}_i)^2}}$	$0.65 < NSE \leq 0.75$	$0.65 < NSE \leq 0.75$
$\boldsymbol{RSR = \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}(X_i - \bar{X}_i)^2}}$	$0.5 < RSR \leq 0.60$	$0.5 < RSR \leq 0.60$
$\boldsymbol{PBIAS = \frac{\sum_{i=1}^{n}(X_i - Y_i) \times 100}{\sum_{i=1}^{n} X_i}}$	$\pm 10\% < PBIAS \leq \pm 15\%$	$\pm 15\% < PBIAS \leq \pm 30\%$

2.3 ANFIS model description and set up

Presented for the first time by Jang (1993), the ANFIS is a data-driven model based on the Takagi-Sugeno's inference system (Takagi & Sugeno, 1985) that combines the best strategies of artificial neural networks and fuzzy logic. The ANFIS model has shown better performance compared to other data driven models for sediment modelling applications (Kisi *et al.*, 2009; Afan *et al.*, 2016; Kaveh *et al.*, 2017). The ANFIS model simulation of suspended sediment in this study was performed using concomitant (i.e. zero lag) variables: precipitation, streamflow and the Watershed Vulnerability Index (Sirabahenda *et al.* 2017). The development of the Watershed Vulnerability Index is based on the key factors of the Universal Soil Loss Equation (USLE) such as the soil erodibility factor *K* with the crops and management factor *C*. The use of the Watershed Vulnerability Index, as an additional predictor, allows the ANFIS model to account for the spatial and seasonal variability of the land-use and soil characteristics in the estimation of SSC (Sirabahenda *et al.*, 2017).

Fuzzy inference calculations were performed using Genifis1 and Evalfis functions incorporated in Matlab's fuzzy logic toolbox (MathWorks, 2015). The ANFIS training is based on a hybrid algorithm allowing error minimisation and used the least square estimator and the gradient descent method to adjust consequences and premise parameters by adapting the connection weights. For comparison, the daily datasets were split into two blocks (for training and test phases) considering the same period and the same assessment criteria for the model performance as in SWAT model simulation.

2.4 Buffer strip scenarios

The legislatively mandated riparian buffer strip width for Mill Watershed was targeted to be extended for sediment loads reduction in the river. Thus, buffer strip widths varying from 15 m (current regulated width) to 100 m were considered for this study. Percentage agricultural area associated with the increase in buffer strip width was computed using Geoprocessing tools 'buffer' and 'clip' in ArcGIS for the watershed studied. Then, the decreased percentage area of agriculture was calculated by dividing the agriculture surface area within every projected buffer strip by total agricultural surface area.

Different buffer width scenarios were simulated using hydro-meteorological data for the validation period. For the ANFIS model, the effect of agricultural area change on sediments loads was tested by modifying the Watershed Vulnerability Index. The value of this index changed as a function of agricultural area associated with the prescribed buffer widths. Similarly, land use in the SWAT model was updated by decreasing agriculture area and increasing the forested area by the same percentage from the watershed data in the ArcSWAT tool before every simulation. Finally, the estimated sediment trapping efficiency was quantified as the difference between sediment loads simulated by both models under the projected riparian strip width and its current conditions.

3 Results

3.1 SWAT and ANFIS sediment simulation results

The first output calibrated for the SWAT model was the streamflow with NSE values of 0.81 and 0.78 respectively for the calibration and validation periods. The RSR and PBIAS were respectively 0.53 and 17.6% for the model calibration period, while they were respectively 0.55 and 24.4% for the validation period. Those quantitative statistics indicated a good performance rating according to the ranges of statistics values recommended (Table 3) and reported for monthly time steps by Moriasi *et al.* (2007). However, streamflows are under-predicted by the SWAT model, similar to results reported by Anaba *et al.* (2017). Factors that most influence streamflow underestimation could be the limitations from the use of SCS Curve numbers (CN2) for days with several downpours for surface runoff calculation (Qiu *et al.*, 2012; Abbaspour *et al.*, 2015) and the spatial variability of precipitation that was not fully captured by the relatively distant rain gauges.

For SSC estimations, Figure 3 shows the time series of flow, precipitation and SSC for calibration phase and validation phase. Low SSC values were often overestimated by both models. For events with high SSC, the ANFIS model predicted SSC more accurately than the SWAT model, although both models underestimated most peaks. The SSC underestimation for high concentrations by SWAT may be due to the simulated streamflow underestimation related to the limitations of the surface runoff calibration processes. Figure 4 and Figure 5 show respectively the log-scaled scatterplots of predicted SSC versus observed SSC for SWAT and ANFIS models. Their high slope and low y-intercept of the best-fit regression line indicated that those models reproduce relatively well the magnitudes of the observed SSC (Willmott, 1981). Performance criteria calculated from daily predicted SSC are presented in Table 4 and their values are all higher than the monthly standards suggested by Moriasi *et al.* (2007).

Please include Figure 2 here.

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Table 4. Model performance evaluation calculated using daily values.

		Statistical performances indicators					
		NSE		RSR		PBIAS	
Variable		calibration	validation	calibration	validation	calibration	validation
Sediment	SWAT	0.76	0.71	0.49	0.56	19.6	23.5
	ANFIS	0.79	0.75	0.45	0.49	15.2	19.7

Those model performance indicators suggest that the ANFIS model used in combination with the Watershed Vulnerability Index can be an alternative and efficient tool to predict SSC comparatively to SWAT model for the Mill River. Although both models have predictive capacity, ANFIS outperformed SWAT. It was found also by Roushangar *et al.* (2014) that ANFIS models gave more accurate total bed material load transport rates than a deterministic model for the Qotur River in Northwestern Iran.

The ANFIS model estimated a total sediment load of 6561 tonnes with an overestimation of 1.7 % during calibration phase and with an underestimation of 13% during validation, compared to the total sediment load observed. The SWAT model estimated the total sediment load as 4836 tonnes with an underestimation of 24 % and 22% compared to the total sediment load observed for calibration and validation phases, respectively.

3.2 Riparian strip effective width and sediment retention rate

The change in simulated sediment retention rates were 30.5 % and 36.2 % of the total stream sediment load for the 100 m wide forested buffer strip for the SWAT and ANFIS models, respectively. These sediment trapping rates represent the net benefit over what the Mill watershed presently has with 15 m buffer strips. The sediment retention rate increases initially with buffer width and starts to reach a plateau for widths above 50 m. There is a diminishing benefit in making the riparian buffer strip wider than 50 m. Thus, by doubling the buffer width from 50 m to 100 m, there is only an increase of sediment retention rate of 4.6 % for the SWAT model and 4.0 % for the ANFIS model. Figure 5shows the variation of sediment trapping efficiency and the decreased percentage area of agriculture in function of the increased buffer widths (i.e. additional buffer width from the original 15 m). An exponential model was also fitted to the simulated retention rates as a function of the increased buffer widths. The equations, provided in Figure 5, can be used by managers to interpolate between the modelled retention rates. Based on the calculation with these equations, Table 5 provides an example of a summary of buffer strip widths (including the original 15 m) and associated target percentages of the theoretical maximum sediment retention that could be used by water resources management to support informed decision-making.

Table 5. Total buffer strip widths required for target percentages of sediment reduction**.**

Additional sediment retention above current (percentage of maximum) [%]	Total Buffer Strip widths required	
	ANFIS [m]	SWAT [m]
10	17.7	18.0
25	22.5	23.1
50	32.6	33.8
75	48.4	49.8
90	65.0	65.6

Please include Figure 5 here.

4.0 Discussion

The fact that ANFIS slightly outperforms SWAT may be in part caused by the differences in model inputs. While SWAT simulates flows and subsequently uses these simulated values as an input to the sediment model, ANFIS used measured flows to accomplish the same. Two of the input variables for the ANFIS model are correlated (precipitation and discharge), but complementary, given that precipitation can mobilize sediments in the drainage basin and flow modulates concentrations and downstream transport. ANFIS may be benefiting from the fact that measured rainfall is not transformed into flows within the model, as in SWAT. It should be noted that intra-annual variability in individual crop types has not been considered for SWAT, as these data were not available. However, as explained by Sirabahenda *et al*. (2017), the Watershed Vulnerability Index varies throughout the growth season. Both K and C factors included in the Index account for seasonal variability in rainfall erosivity index and crop stages. This varying index in ANFIS may also be one of the reasons why it outperformed SWAT.

The sediment load underestimation at high SCC by the SWAT model could be linked to underestimation of runoff and/or the difficulty of SWAT to adequately predict the contribution of stream bank soil losses (Zaimes *et al.*, 2004). In fact, this limitation has been recognized in other studies (e.g. Ricci *et al.*, 2018) and has led to the development of a streambank erosion module (Narasimhan et al., 2017). When land use is changed in SWAT, the value of curve number (CN) and crop factor (C) are updated. Therefore, changes in land use in SWAT (e.g., increasing buffer widths) has an impact on sediment trapping, but also on sediment generation. The variations in soil aggregate stability during freeze and thaw periods may also affect runoff and soil erosion (Hayhoe *et al.*, 1992; Starkloff *et al.*, 2018). It has also been noted by Edwards and Burney (1989) that the snowmelt and prolonged low-intensity rains yield greater sediment loss for PEI soils in early spring.

The comparative analysis also shows that the ANFIS model gives an average of 6.4 % higher sediment retention ratios than SWAT model. This relatively small difference can be explained by uncertainties related to input data and to the limitations inherent to the mathematical conceptualization of both models. The ANFIS model works as a black box (Wang, 2006) and the parameters have no interpretable meaning in terms of sediment transport processes like sediment resuspension or deposition phenomena. The ANFIS model needs large datasets for the learning phase. Hence, when the time series are relatively short, the model has its limits and over-parametrization can occur that may lead to overfit (Nayak & Jain, 2011;

Sanikhani & Kisi, 2012). Conversely, the under estimation of the runoff factors by the SWAT model results in under estimation of sediment loads implicitly during simulation. Tibebe and Bewket (2011) were faced with a similar challenge in their implementation of SWAT in Ethiopia. Peak runoff was underestimated by the model, and so were the associated sediment loads. Recent improvements in SWAT by (Cibin et al. 2018) may provide a different outcome in future comparative studies.

The main limitation of this study with regards to the assessment of trapping efficiency of buffer strips is the fact that our implementations of both SWAT and ANFIS did not account directly for the fact that buffer width increases occur at the edges of fields. Although this fact can be rightly considered as a model shortfall, it allows for a more direct comparison of the two approaches, given that the ANFIS model is not structured to specifically indicate the location of buffer strips. Other factors related to local conditions not fully captured by our models may affect the sediment trapping efficiency such as steep slopes, sediment grain size distribution and footpaths in the riparian buffer strip that may create preferential flows/gullies (Wenger, 1999; Shan *et al.*, 2014). Fischer and Fischenich (2000) noted that the wide buffers strips with optimal conditions can often be compromised by improper practices. It should also be mentioned that the buffer strip vegetation is dominated by trees and that future mitigation measures should be considering a more suitable mix of plants (Betrie *et al.*, 2011; Moriasi *et al.*, 2011; Zaimes & Schultz, 2015). For instance, Shan et al. (2014) found that an average effective width was of the order of 58 m using SWAT and a Riparian Ecosystem Management Model during a research study in the Three Gorges Reservoir area (China). This result is similar to the conclusion of the present study. However, they also indicated that wider widths were required for areas with steeper slopes or finer textured soil. Other reviewed studies noted that the sediment retention increases with riparian width but not infinitely and the effective riparian buffer strip width is site-specific (Parkyn, 2004).

In spite of these restrictions, both models allowed us to quantitatively investigate the effectiveness of buffer strip widths on sediment trapping efficiency. The asymptotic behavior of the curve relating trapping efficiency to buffer widths, which indicates that beyond a certain threshold, the gain in extending the buffer strip is minimal was also noted in other studies. For instance, Cho et al. (2010) used the SWAT model in Little River Experimental Watershed (Georgia, U.S.A) and found that trapping efficiency reached a maximum value at 30 m and remained constant for wider buffer strips. Similar results were also found by Zhang et al. (2017) for sediment retention, but also for the reduction of total nitrogen and total phosphorous. These authors reached a conclusion similar to ours; in general, extending the buffer strip width over 50 m in conditions like those encountered on PEI does not generate much additional gain in sediment retention. Selecting 50 m as a buffer width would be more conservative than what is recommended by Canadian federal authorities. Indeed, Agriculture and Agri-Food Canada recommends a buffer width varying between 10-30 m for sediment retention (http://www.agr.gc.ca/eng/science-and-innovation). The final choice of the optimum buffer width would require evaluating the benefit of that sediment retention – both for the farmers who get to keep their soil - and for improved quality of surface waters.

5.0 Conclusion

This study explored the effectiveness of two models: SWAT and ANFIS to simulate SSC and loads and their sensitivity to land use parameter changes. Predicted SSC values were close to measured SSC values in most instances for both models for the calibration and validation periods, but the values of the quantitative statistics were better for the ANFIS model compared to the SWAT model. Although both models underestimated sediment loads, the ANFIS model was less biased than SWAT. Both models suggested the same optimal forested riparian zone width for sediment removal with a slight difference for sediment trapping ratios, indicating credible performance of ANFIS to simulate the effects of land occupation variation on sediment. The models suggest that increasing the buffer width beyond 50 m yields only minor improvements in sediment trapping.

This study was an exploration case to test the reliability of an empirical model in comparison with a deterministic model for sediment estimation for future management of sediment delivery factors, like land-use/land-cover, in agricultural watersheds. The simulated loads obtained with the two modelling approaches constitute helpful information for watershed managers and stakeholders to plan beneficial management practices and to formulate their environmental policies for riparian zones. Since both models provide first approximation estimations, further investigation should be conducted with a long-term monitoring campaign of SSC to make a comparison with empirical data on the effectiveness of different buffer widths on sediment retention. It is likely that limitations of the ANFIS model would be further highlighted in a more detailed analysis that would account for inter-seasonal shifts in land use practices and alternative riparian zone designed such as zonation within the buffer strip that includes different types of vegetation (gradient of grass, shrubs and trees). However, this study showed that an empirical model can provide a first assessment of the benefits of riparian zones in agriculture-dominated watersheds.

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References

Abbaspour KC, Rouholahnejad E, Vaghefi S, Srinivasan R, Yang H & Kløve B (2015) A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology* 524:733-752.

Afan HA, El-shafie A, Mohtar WHMW & Yaseen ZM (2016) Past, present and prospect of an Artificial Intelligence (AI) based model for sediment transport prediction. *Journal of Hydrology* 541:902-913.

Agriculture and Agri-food Canada. 2019. http://www.agr.gc.ca/eng/science-and-innovation/agricultural-practices/agroforestry/shelterbelt-planning-and-establishment/design/riparian-buffers/?id=1344888191892. Accessed 19 August 2019.

Alberto A, St-Hilaire A, Courtenay SC & van den Heuvel MR (2016) Monitoring stream sediment loads in response to agriculture in Prince Edward Island, Canada. *Environmental Monitoring and Assessment* 188(7):415.

Anaba LA, Banadda N, Kiggundu N, Wanyama J, Engel B & Moriasi D (2017) *Application of SWAT to Assess the Effects of Land Use Change in the Murchison Bay Catchment in Uganda.* 24-40 p

Arnold JG & Allen PM (1999) Automated methods for estimating baseflow and groundwater recharge from streamflow records. *Journal of the American Water Resources Association* 35(2):411-424.

Arnold JG, Allen PM, Muttiah R & Bernhardt G (1995) Automated Base Flow Separation and Recession Analysis Techniques. *Groundwater* 33(6):1010-1018.

Arnold, Jeff Moriasi, Daniel Gassman, Philip Abbaspour, Karim White, Michael Srinivasan, Raghavan Santhi, Chinnasamy Harmel, R. van Griensven, Ann Van Liew, Michael Kannan, Narayanan Jha, Manoj. (2012). SWAT: Model use, calibration, and validation. 55. 10.13031/2013.42256.

Bagnold R (1977) Bed load transport by natural rivers. *Water resources research* 13(2):303-312.

Beaudry F (2017) *Sediment Pollution.* https://www.thoughtco.com/water-pollution-sediment-1204128 (Consulted June 4, 2018)

Betrie GD, Mohamed YA, van Griensven A & Srinivasan R (2011) Sediment management modelling in the Blue Nile Basin using SWAT model. *Hydrol. Earth Syst. Sci.* 15(3):807-818.

Beyer J, Petersen K, Song Y, Ruus A, Grung M, Bakke T & Tollefsen KE (2014) Environmental risk assessment of combined effects in aquatic ecotoxicology: A discussion paper. *Marine Environmental Research* 96:81-91.

Borin M, Passoni M, Thiene M & Tempesta T (2010) Multiple functions of buffer strips in farming areas. *European Journal of Agronomy* 32(1):103-111.

Chang C-L, Hsu Y-S, Lee B-J, Wang C-Y & Weng L-J (2011) A cost-benefit analysis for the implementation of riparian buffer strips in the Shihmen reservoir watershed. *International Journal of Sediment Research* 26(3):395-401.

Cho, J., Lowrance, R. R., Bosch, D. D., Strickland, T. C., Her, Y., & Vellidis, G. (2010). Effect of watershed subdivision and filter width on SWAT simulation of a coastal plain watershed. Journal of the *American Water Resources Association*, 46(3), 586-602. https://doi.org/10.1111/j.1752-1688.2010.00436

Coffin MR, Courtenay SC, Pater CC & van den Heuvel MR (2018) An empirical model using dissolved oxygen as an indicator for eutrophication at a regional scale. *Marine Pollution Bulletin* 133:261-270.

Edwards LM & Burney JR (1989) The effet of antecedent freeze-thaw frequency on runoff and soil loss from frozen soil with and without subsoil compaction and ground cover. *Canadian Journal of Soil Science* 69(4):799-811.

FAO & IWMI (2017) Water pollution from agriculture : a global review. *Rome, Food and Agriculture Organization of the United Nations (FAO) and Colombo, International Water Management Institute*.

Fischer RA & Fischenich JC (2000) Design recommendations for riparian corridors and vegetated buffer strips. U.S. Army Engineer Research and Development Center. *Environmental Laboratory. Vicksburg, MS*.

Gupta HV, Sorooshian S & Yapo PO (1999) Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. *Journal of Hydrologic Engineering* 4(2):135-143.

Hamaamin Y, Nejadhashemi A, Zhang Z, Giri S & Woznicki S (2016) Bayesian Regression and Neuro-Fuzzy Methods Reliability Assessment for Estimating Streamflow. *Water* 8(7):287.

Hawes E & Smith M (2005) *Riparian Buffer Zones: Functions and Recommended Widths.* http://www.eightmileriver.org/resources/digital_library/appendicies/09c3_Riparian%20Buffer%20Science_YALE.pdf (Consulté le 25.03.2018)

Hayhoe H, Pelletier R & Moggridge S (1992) Analysis of freeze-thaw cycles and rainfall on frozen soil at 7 Canadian locations. *Canadian Agricultural Engineering* 34(2):135-142.

Hould-Gosselin G, Rousseau AN, Gumiere SJ, Hallema DW, Ratté-Fortin C, Thériault G & Bochove E (2016) Modeling the sediment yield and the impact of vegetated filters using an event-based soil erosion model—a case study of a small Canadian watershed. *Hydrological Processes* 30(16):2835-2850.

Jang J-S (1993) ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics* 23(3):665-685.

Kadokami K, Li X, Pan S, Ueda N, Hamada K, Jinya D & Iwamura T (2013) Screening analysis of hundreds of sediment pollutants and evaluation of their effects on benthic organisms in Dokai Bay, Japan. *Chemosphere* 90(2):721-728.

Kaveh K, Duc Bui M & Rutschmann P (2017) A comparative study of three different learning algorithms applied to ANFIS for predicting daily suspended sediment concentration. *International Journal of Sediment Research* 32(3):340-350.

Keesstra S, Pereira P, Novara A, Brevik EC, Azorin-Molina C, Parras-Alcántara L, Jordán A & Cerdà A (2016) Effects of soil management techniques on soil water erosion in apricot orchards. *Science of The Total Environment* 551-552:357-366.

Kisi O, Haktanir T, Ardiclioglu M, Ozturk O, Yalcin E & Uludag S (2009) Adaptive neuro-fuzzy computing technique for suspended sediment estimation. *Advances in Engineering Software* 40(6):438-444.

Kuichling E (1889) The Relation between the Rainfall and the Discharge of Sewers in Populous Districts. *Transactions of ASCE, 20, 1-60.*

Liu X, Zhang X & Zhang M (2008) Major Factors Influencing the Efficacy of Vegetated Buffers on Sediment Trapping: A Review and Analysis. *Journal of Environmental Quality* 37(5):1667-1674.

Mankin KR, Ngandu DM, Barden CJ, Hutchinson SL & Geyer WA (2007) Grass-Shrub Riparian Buffer Removal of Sediment, Phosphorus, and Nitrogen From Simulated Runoff1. *JAWRA Journal of the American Water Resources Association* 43(5):1108-1116.

MathWorks M (2015) SIMULINK for technical computing. *Avaliable on* http://www. *mathworks. com*.

Mello Kd, Randhir TO, Valente RA & Vettorazzi CA (2017) Riparian restoration for protecting water quality in tropical agricultural watersheds. *Ecological Engineering* 108:514-524.

Mello Kd, Valente RA, Randhir TO, dos Santos ACA & Vettorazzi CA (2018) Effects of land use and land cover on water quality of low-order streams in Southeastern Brazil: Watershed versus riparian zone. *CATENA* 167:130-138.

Miller JJ, Curtis T, Chanasyk DS & Reedyk S (2015) Influence of mowing and narrow grass buffer widths on reductions in sediment, nutrients, and bacteria in surface runoff. *Canadian Journal of Soil Science* 95(2):139-151.

Monteiro JAF, Kamali B, Srinivasan R, Abbaspour K & Gücker B (2016) Modelling the effect of riparian vegetation restoration on sediment transport in a human-impacted Brazilian catchment. *Ecohydrology* 9(7):1289-1303.

Monteith JL (1965) Evaporation and the environment. p.205-234. In The state and movement of water in living organisms.19th Symposia of the Society for Experimental Biology. Cambridge Univ.Press, London, UK.

Montgomery DR (2007) Soil erosion and agricultural sustainability. *Proceedings of the National Academy of Sciences* 104(33):13268-13272.

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD & Veith TL (2007) Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. *Transactions of the ASABE* 50(3):885.

Moriasi DN, Steiner JL & Arnold JG (2011) Sediment measurement and transport modeling: Impact of riparian and filter strip buffers. *Journal of Environmental Quality* 40:807-814.

Narasimhan, B, Allen, P M, Coffman, S V, Arnold, J G, & Srinivasan, R. (2017). Development and Testing of a Physically Based Model of Streambank Erosion for Coupling with a Basin-Scale Hydrologic Model SWAT. *Journal of the American Water Resources Association,* 53(2), 344-364. doi:10.1111/1752-1688.12505

Nash JE & Sutcliffe JV (1970) River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology* 10(3):282-290.

Nayak PC & Jain SK (2011) Modelling runoff and sediment rate using aneuro-fuzzy technique. *Proceedings of the Institution of Civil Engineers - Water Management* 164(4):201-209.

Neitsch S, Arnold J, Kiniry Jea, Srinivasan R & Williams J (2002) Soil and water assessment tool user’s manual version 2000. *GSWRL report* 202(02-06).

Neitsch SL, Arnold JG, Kiniry JR & Williams JR (2011) Soil & Water Assessment Tool Theoretical Documentation Version 2009. Technical Report No 406, Texas Water Resources Institute, College Station, p 1-647.

Pacheko, F A L, S G P Varandas, L F Sanches Fernandes, R F Valle Junior. (2014). Soil losses in rural watersheds with environmental land use conflicts. *Science of the Total Environment* 485-486(1): 110-120.

Parkyn S (2004) Review of riparian buffer zone effectiveness. In: Ministry of Agriculture and Forestry Technical Paper No. 2004/05, Wellington, New Zealand.

PEI Department of Environment/ Energy & Forestry and Resource Inventory (2010) Corporated Land Use Inventory 2010. *www.gov.pe.ca/gis*.

Qiu L-j, Zheng F-l & Yin R-s (2012) SWAT-based runoff and sediment simulation in a small watershed, the loessial hilly-gullied region of China: capabilities and challenges. *International Journal of Sediment Research* 27(2):226-234.

Ramskov T, Forbes VE, Gilliland D & Selck H (2015) Accumulation and effects of sediment-associated silver nanoparticles to sediment-dwelling invertebrates. *Aquatic Toxicology* 166:96-105.

Research Branch Agriculture Canada/PEI Department of Agriculture (1994) Soil Survey of PEI. *www.gov.pe.ca/gis*.

Restrepo JD & Escobar HA (2018) Sediment load trends in the Magdalena River basin (1980–2010): Anthropogenic and climate-induced causes. *Geomorphology* 302:76-91.

Ricci, GF, De Girolamo, AM, Abdelwahab, OMM, Gentile, F. (2018). Identifying sediment source areas in a Mediterranean watershed using the SWAT model. *Land Degradation and Development*. 29, 1233-1248. http://dx.doi.org/10.1002/ldr.2889.

Romano G, Abdelwahab OMM & Gentile F (2018) Modeling land use changes and their impact on sediment load in a Mediterranean watershed. *CATENA* 163:342-353.

Roushangar K, Mehrabani FV & Shiri J (2014) Modeling river total bed material load discharge using artificial intelligence approaches (based on conceptual inputs). *Journal of Hydrology* 514:114-122.

Sahu M & R. Gu R (2009) Modeling the effects of riparian buffer zone and contour strips on stream water quality. *Ecological Engineering* 35(8): 1167-1177 p

Sanikhani H & Kisi O (2012) River Flow Estimation and Forecasting by Using Two Different Adaptive Neuro-Fuzzy Approaches. *Water Resources Management* 26(6):1715-1729.

Schmidt AH, Gonzalez VS, Bierman PR, Neilson TB & Rood DH (2018) Agricultural land use doubled sediment loads in western China's rivers. *Anthropocene* 21:95-106.

Shan N, Ruan X-H, Xu J & Pan Z-R (2014) Estimating the optimal width of buffer strip for nonpoint source pollution control in the Three Gorges Reservoir Area, China. *Ecological Modelling* 276:51-63.

Shi P, Zhang Y, Li Z, Li P & Xu G (2017) Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales. *CATENA* 151:182-190.

Sirabahenda Z, St-Hilaire A, Courtenay SC, Alberto A & Van Den Heuvel MR (2017) A modelling approach for estimating suspended sediment concentrations for multiple rivers influenced by agriculture. *Hydrological Sciences Journal* 62(13):2209-2221.

Song B, Zeng G, Gong J, Liang J, Xu P, Liu Z, Zhang Y, Zhang C, Cheng M, Liu Y, Ye S, Yi H & Ren X (2017) Evaluation methods for assessing effectiveness of in situ remediation of soil and sediment contaminated with organic pollutants and heavy metals. *Environment International* 105:43-55.

Starkloff T, Stolte J, Hessel R, Ritsema C & Jetten V (2018) Integrated, spatial distributed modelling of surface runoff and soil erosion during winter and spring. *CATENA* 166:147-157.

Stutter MI, Chardon WJ & Kronvang B (2012) Riparian Buffer Strips as a Multifunctional Management Tool in Agricultural Landscapes: Introduction. *Journal of Environmental Quality* 41(2):297-303.

Sweeney BW & Newbold JD (2014) Streamside Forest Buffer Width Needed to Protect Stream Water Quality, Habitat, and Organisms: A Literature Review. *JAWRA Journal of the American Water Resources Association* 50(3):560-584.

Takagi T & Sugeno M (1985) Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics* SMC-15(1):116-132.

Cibin, Raj, Indrajeet Chaubey, Matthew J. Helmers, K. P. Sudheer, Michael J. White, and Jeffrey G. Arnold. 2018. “An Improved Representation of Vegetative Filter Strips in SWAT.” *Transactions of the ASABE* 61 (3): 1017–24. https://doi.org/10.13031/trans.12661.

Tibebe, D., and W. Bewket. (2011). “Surface Runoff and Soil Erosion Estimation Using the SWAT Model in the Keleta Watershed, Ethiopia.” *Land Degradation & Development* 22 (6): 551–64. https://doi.org/10.1002/ldr.1034.

Tim, U S, R Jolly, H H Liao. (1995). Impact of landscape feature and feature placement on agricultural non-point-source-pollution control. *Journal of Water Resources Planning and Management* 121(6): 463-470.

U.S. Environmental Protection Agency (2000) National Water Quality Inventory. 1998 Report to Congress, USPA 841-R-00-001, Washington DC.

USDA Soil Conservation Service (1972) National Engineering Handbook Section 4 Hydrology, Chapters 4-10.

Valero C, Alonso C, De Miguel RJ, Fernandez-Delgado C & Garcia de Jalon D (2017) Response of fish communities in rivers subjected to a high sediment load. *Limnologica - Ecology and Management of Inland Waters* 62:142-150.

van der Poll HW (1983) Geology of Prince Edward Island. Department of Forestry and Forestry Energy and Minerals Branch, 66 p. Province of Prince Edward Island. Report 83-1.

van Vliet J, Bregt A, Brown D, van Delden H, Heckbert S & Verburg P (2016) *A review of current calibration and validation practices in land-change modeling.* 174-182 p

Vigiak O, Malagó A, Bouraoui F, Grizzetti B, Weissteiner CJ & Pastori M (2016) Impact of current riparian land on sediment retention in the Danube River Basin. *Sustainability of Water Quality and Ecology* 8:30-49.

Wang W (2006) *Stochasticity, Nonlinearity and Forecasting of Streamflow Processes.* IOS Press, Amsterdam,The Netherlands.

Wenger S (1999) *A Review of the Scientific Literature on Riparian Buffer Width, Extent and Vegetation.* Office of Public Service & Outreach, Athens (59 pp.).

Williams JR (1969) Flood routing with variable travel time or variable storage coefficients. *Transactions of the ASAE* 12(1):100-103.

Williams JR (1995) Chapter 25. The Epic Model. p 909-1000. In Computer Modeles of Watershed Hydrology. Waters Resources Publications. Highlands Ranch, CO

Willmott CJ (1981) On the validation of models. *Physical Geography* 2(2):184-194.

Zaimes G, Schultz R & Isenhart T (2004) Stream bank erosion adjacent to riparian forest buffers, row-crop fields, and continuously-grazed pastures along Bear Creek in central Iowa. *Journal of Soil and Water Conservation* 59(1):19-27.

Zaimes GN & Schultz RC (2015) Riparian land-use impacts on bank erosion and deposition of an incised stream in north-central Iowa, USA. *CATENA* 125:61-73.

Zhang, C., Li, S., Qi, J., Xing, Z., & Meng, F. (2017). Assessing impacts of riparian buffer zones on sediment and nutrient loadings into streams at watershed scale using an integrated REMM-SWAT model. *Hydrological Processes*, 31(4), 916-924. https://doi.org/10.1002/hyp.11073.

FIGURE CAPTIONS

Figure 1. Location of PEI in Canada (a), Mill River Watershed location (b), elevation (c) land use (d) and slope (e).

Figure 2 Time series plot of observed flow (blue), precipitation (green) and SSC for Calibration phase (a) and for validation phase (b)

Figure 3. Scatter plot of observed versus simulated SSC for SWAT model.

Figure 4. Scatter plot of observed versus simulated SSC for ANFIS model.

Figure 5. Sediment trapping efficiency versus the increased riparian buffer width.