

Original Research Article

Developing a Decision Support Tool for Assessing Land Use Change and BMPs in Ungauged Watersheds Based on Decision Rules Provided by SWAT Simulation

Junyu Qi^a, Sheng Li^{b,c}, Charles P.-A. Bourque^b, Zisheng Xing^{b,c}, and Fan-Rui Meng^{b,*}

^a Earth System Science Interdisciplinary Center, University of Maryland, College Park,
5825 University Research Ct, College Park, MD, 20740, USA

^b Faculty of Forestry and Environmental Management, University of New Brunswick,
P.O. Box 44400, 28 Dineen Drive, Fredericton, NB, E3B 5A3,
Canada

^c Potato Research Centre, Agriculture and Agri-Food Canada, P.O. Box 20280, 850
Lincoln Road, Fredericton, NB, E3B 4Z7, Canada

***Corresponding author:** Fan-Rui Meng, Tel.: +1 506 453 4921, E-mail: fmeng@unb.ca

1 **Abstract**

2 Decision making on water resources management at ungauged, especially large-scale
3 watersheds relies on hydrological modeling. Physically-based distributed hydrological
4 models require complicated setup, calibration and validation processes, which may delay
5 their acceptance among decision makers. This study presents an approach to develop a
6 simple decision support tool (DST) for decision makers and economists to evaluate multi-
7 year impacts of land use change and BMPs on water quantity and quality for ungauged
8 watersheds. The example DST developed in the present study was based on statistical
9 equations derived from Soil and Water Assessment Tool (SWAT) simulations applied to
10 a small experimental watershed in northwest New Brunswick. The DST was
11 subsequently tested against field measurements and SWAT-model simulations for a
12 larger watershed. Results from DST could reproduce both field data and model
13 simulations of annual stream discharge and sediment and nutrient loadings. The relative
14 error of mean annual discharge and sediment, nitrate-nitrogen, and soluble-phosphorus
15 loadings were -6, -52, 27, and -16%, respectively, for long-term simulation. Compared
16 with SWAT, DST has fewer input requirements and can be applied to multiple
17 watersheds without additional calibration. Also, scenario analyses with DST can be
18 directly conducted for different combinations of land use and BMPs without complex
19 model setup procedures. The approach in developing DST can be applied to other regions
20 of the world because of its flexible structure.

21 **Keywords:** multiple regression; hydrological model; erosion; nitrate leaching;
22 geographic information system

23

24 **1. Introduction**

25 Pollution from nonpoint sources poses a significant threat to ecosystems and plant and
26 animal communities (Vörösmarty et al., 2010). Nonpoint sources of sediment, nutrients,
27 and pesticides, primarily from agricultural lands, have been identified as major
28 contributors to water quality degradation (Ongley et al., 2010; Zhang et al., 2004). These
29 pollutants are difficult to control because they come from many sources (Quan and Yan,
30 2001). Practices such as strip cropping, terracing, crop rotation, and nutrient management
31 can be developed to prevent soil erosion and reduce the movement of nutrients and
32 pesticides from agricultural lands to aquatic ecosystems (D'Arcy and Frost, 2001). These
33 pollution-prevention methods, known as best management practices (BMPs), are
34 intended to minimize the negative environmental impact of agricultural activities, while
35 maintaining land productivity. Reliable information on the impacts of land use change
36 and BMPs on water quantity and quality is critical to watershed management
37 (Panagopoulos et al., 2011).

38 Many studies have been conducted to evaluate the impact of land use change and
39 BMPs on water quality based on field experiments (Novara et al., 2011; Pimentel and
40 Krummel, 1987; Sadeghi et al., 2012; Turkelboom et al., 1997; Urbonas, 1994).
41 Monitoring systems have been established to assess the impact of land use change and
42 BMPs on water resources in order to capture the spatial and temporal variation in soil,
43 climate, and topographic conditions in watersheds (Veldkamp and Lambin, 2001).
44 Statistical models developed from field data from small watersheds are usually assumed
45 to apply to large watersheds (Blöschl and Sivapalan, 1995; Blöschl and Grayson, 2001).
46 Although it is not difficult to quantify soil erosion and chemical loadings in experimental

47 plots, it is time-consuming and expensive (Mostaghimi et al., 1997). Clearly, it is not
48 practical to conduct field experiments for every possible combination of land use and
49 BMPs, under different biophysical conditions. As a result, it is unlikely sufficient field
50 data could be obtained to develop management plans and conduct cost-benefit analyses.
51 In addition, statistical models could be potentially derived from experiments; however, it
52 is difficult to establish cause-and-effect relationships between BMPs and water quality
53 variables under varied biophysical conditions or to quantify the impact of combined land
54 use and BMPs on water quality at the watershed scale (Renschler and Lee, 2005).

55 Process-based models of hydrology can be used to extrapolate field data to fill data
56 gaps (Borah and Bera, 2003; Borah and Bera, 2004; Singh, 1995; Singh and Frevert,
57 2005; Singh and Woolhiser, 2002). These process-based models provide quantitative
58 information that is usually difficult to obtain from field experiments (Borah et al., 2002).
59 For example, ANSWERS (Beasley et al., 1980), CREAMS (Knisel, 1980), GLEAMS
60 (Leonard et al., 1987), AGNPS (Young et al., 1989), EPIC (Sharpley and Williams,
61 1990), and SWAT (Arnold et al., 1998) have been used to understand surface runoff, soil
62 erosion, nutrient leaching, and pollutant-transport processes. However, these process-
63 based models require extensive input data and complex calibration procedures (Liu et al.,
64 2015); watersheds with sufficient data to calibrate and validate these models are normally
65 small, resulting in lack of representation at large spatial scales. Furthermore, once a
66 model is calibrated, parameters become watershed-specific, which cannot be easily
67 extended to other watersheds. In addition, these models require specialized expertise,
68 which prevents non-expert decision makers and economists to use them (Viavattene et al.,
69 2008).

70 A decision support tool could be developed by combining “decision rules” with
71 geographic information systems (GIS) for water quality assessment in large ungauged
72 watersheds. The “decision rules” could be based on regression equations derived from
73 field experiments (Renschler and Harbor, 2002), or they could be defined simply as
74 constants based on expert knowledge. Alternatively, simulations from a well-calibrated
75 hydrological model could be used to develop statistical equation-based “decision rules”.
76 Apart from defining “decision rules” at each grid cell, to assess water quantity and
77 quality in streams or at subbasin/watershed outlets, the decision support tool should
78 consider discharge, sediment, and nutrient routing within the watershed. For example, a
79 commonly used routing method for sediments is the sediment-delivery ratio (SDR)
80 method, which is widely employed in many GIS-based erosion models (May and Place,
81 2010; Wilson et al., 2001; Zhao et al., 2010). For discharge, a simple summation routing
82 at the outlet produces acceptable accuracy for small- and medium-sized watersheds,
83 considering that there is negligible water losses from surface runoff and stream flow. For
84 large watersheds, water losses are generally greater. These water losses can be estimated
85 using simple linear equations. The annual export of nutrients from watersheds (via the
86 nutrient-delivery ratio) has been studied empirically in many studies as nutrient loading
87 per land area (Beaulac and Reckhow, 1982; Endreny and Wood, 2003; Reckhow and
88 Simpson, 1980).

89 A decision support tool developed based on “decision rules” is generally flexible and
90 easy for decision makers and economists to use (Endreny and Wood, 2003). However,
91 their practicality in normal circumstances, particularly with respect to their level of
92 accuracy, needs to be evaluated. In addition, in order to provide sufficient “decision rules”

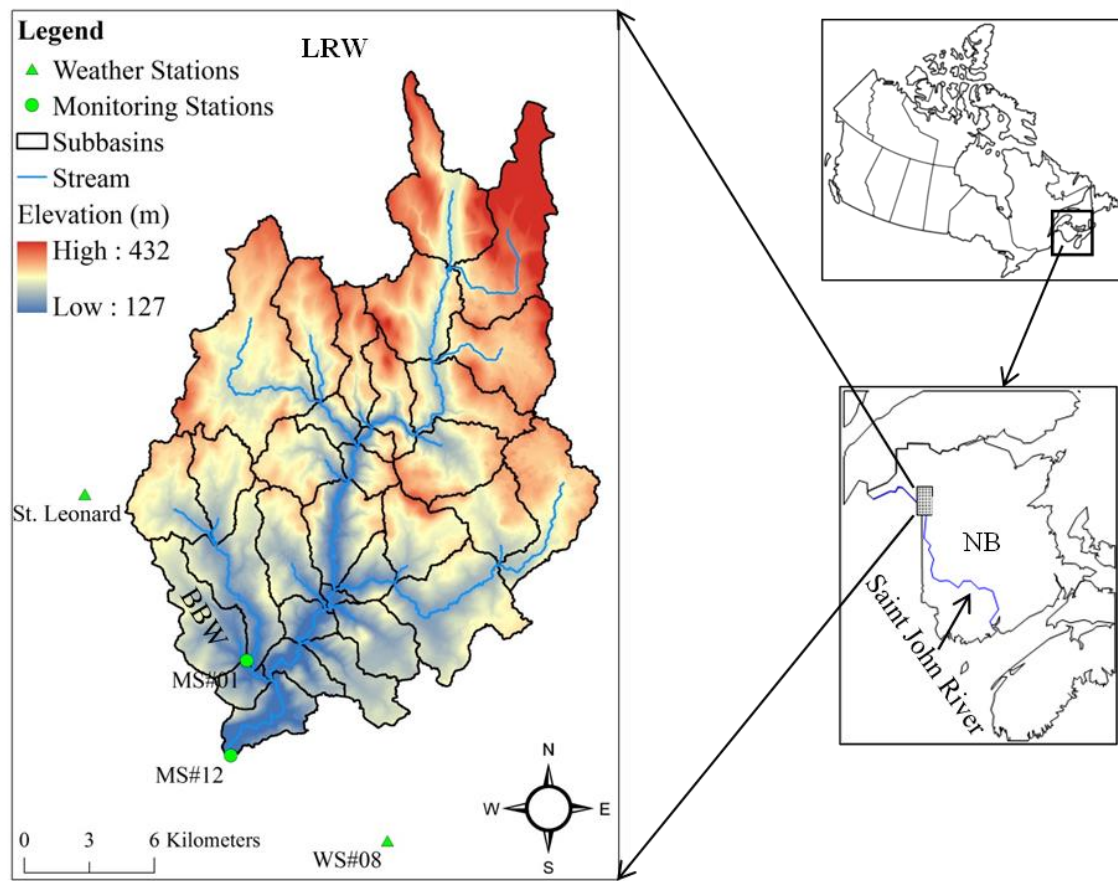
93 with reasonable accuracy, fully validated hydrological models are required to be able to
94 fill data gaps in field experiments. The present study used the Soil and Water Assessment
95 Tool (SWAT) to provide modelled data in the development of the decision support tool.
96 The main objective of the present study is to develop a simple decision support tool with
97 the intent to evaluate the impact of land use change and BMPs on water resources in a
98 large ungauged watershed in New Brunswick, Canada. This paper presents the
99 development and testing of a decision support tool using data from two watersheds in the
100 potato-belt of New Brunswick; one small experimental watershed, with extensive
101 monitoring and field survey data, and a larger watershed containing the smaller
102 watershed. Specifically, this involves: (1) setting up, calibrating, and validating SWAT
103 for a small experimental watershed; (2) developing statistical equations relating water
104 quality and quantity variables with weather, soil, land use information based on SWAT-
105 model simulations for different combinations of land use and BMPs; (3) integrating the
106 statistical equations into a decision support tool with the aid of ArcGIS; and (4) testing
107 the decision support tool against field measurements and model simulations of stream
108 discharge, sediment, and nutrient loadings for a large watershed.

109 **2. Materials and Methods**

110 **2.1 Study Sites and Data Collection**

111 The large watershed of this study is the Little River Watershed (LRW), located in the
112 Upper Saint John River Valley of northwestern New Brunswick, Canada (Fig. 1). It
113 covers an area approximately 380 km² with a mixture of agricultural (16.2%), forest
114 (77%), and residential (6.8%) land uses (Xing et al., 2013). Elevation in the watershed
115 ranges from 127 to 432 m above mean sea level (Fig. 1). The soil in the study sites is

116 classified as mineral, derived from various parent materials. The major associations are
117 Caribou, Carleton, Glassville, Grandfalls, Holmesville, McGee, Muniac, Siegas, Thibault,
118 Undine, Victoria, Waasis, and one organic soil (Fig. 2). The study site belongs to the
119 Upper Saint John River Valley Ecoregion in the Atlantic Maritime Ecozone (Marshall et
120 al., 1999). The climate of the region is considered to be moderately cool boreal with
121 approximately 120 frost-free days, annually (Yang et al., 2009). Daily maximum and
122 minimum temperature are 24 (in July) and -18.1°C (in January) based on Canadian Climate
123 Normals station data at St. Leonard (http://climate.weather.gc.ca/climate_normals). The
124 average temperature is 3.7°C and annual precipitation is 1037.4 mm (Zhao et al., 2008).
125 About one-third of the precipitation is in the form of snow. Snowmelt leads to major
126 surface runoff and groundwater recharge events from March to May (Chow and Rees,
127 2006). The land use and soil maps in the setup of SWAT for LRW were derived from
128 publicly available data [Energy and Resource Development (ERD), New Brunswick; Fig.
129 2].



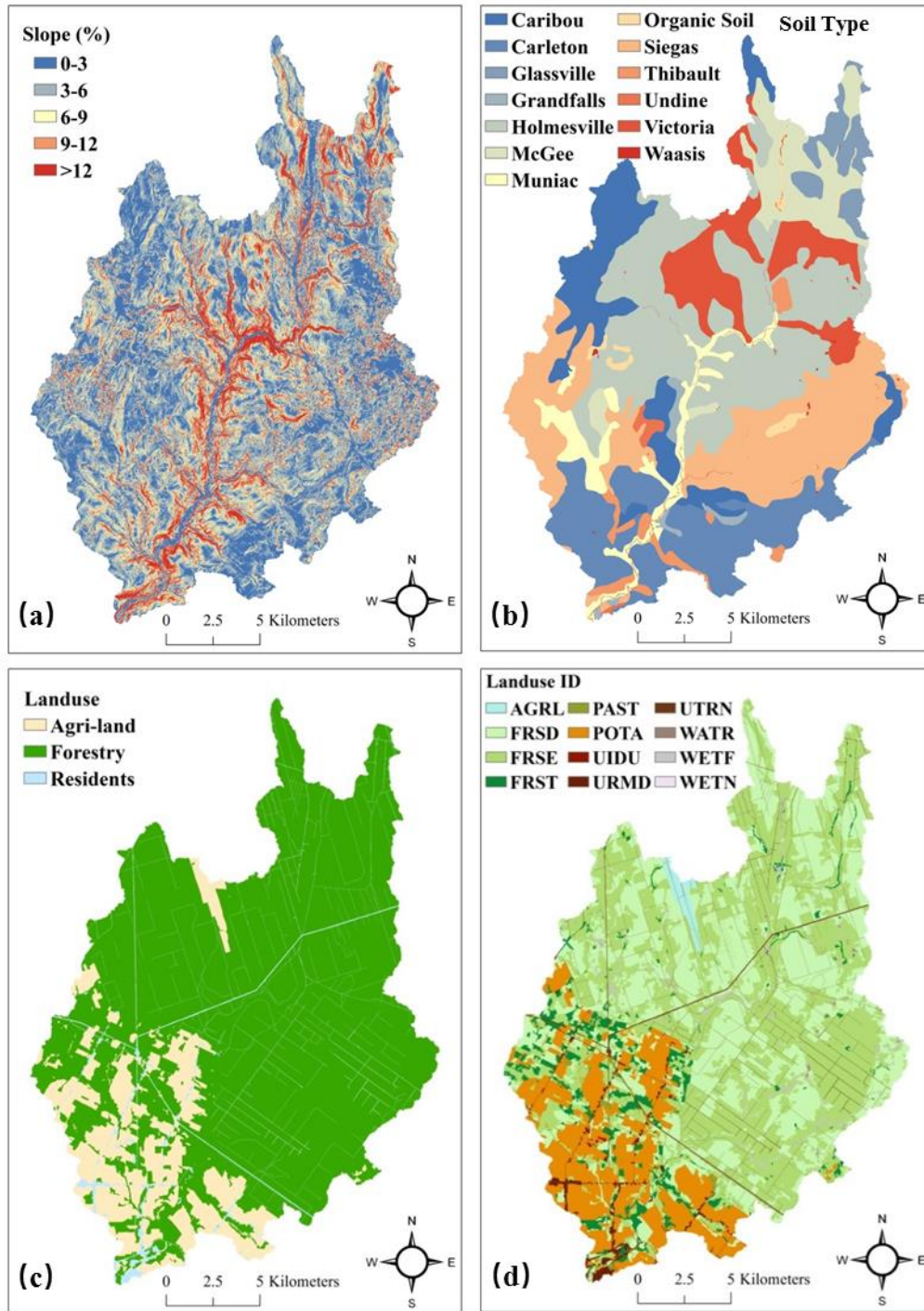
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132 **Fig. 1** Location of the Little River Watershed (LRW) and Black Brook Watershed (BBW)

133 in New Brunswick (NB), Canada and water-monitoring stations #01 and #12 as well as

134 weather stations #08 and St. Leonard. Elevations and subbasins are also shown for LRW.

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136

137 **Fig. 2** Slope classes created using a 10-m resolution LiDAR (Light Detection and
 138 Ranging)-based DEM (Digital Elevation Model), soil and land use maps, and land use
 139 IDs in SWAT (see Table 2 for land use ID meaning).

140 The small experimental watershed of the study is the Black Brook Watershed (BBW),
141 a subbasin of LRW (Fig. 1). The BBW has been studied extensively for more than 20
142 years to evaluate the impact of agriculture on soil erosion and water quality (Chow and
143 Rees, 2006; Li et al., 2014). The watershed covers an area of 14.5 km², with 65% being
144 agriculture land, 21% forest land, and 14% residential areas and wetlands. Slopes vary
145 from 1-6% in the upper basin to 4-9% in the central area. In the lower portion of the
146 watershed, slopes are more strongly rolling at 5-16%. Soil surveys (1:10,000 scale)
147 identified six mineral soils, namely Grandfalls, Holmesville, Interval, Muniac, Siegas,
148 and Undine, and one organic soil, St. Quentin (Mellerowicz, 1993).

149 A water-monitoring station was established at the outlet of BBW in 1992 (MS#01; Fig.
150 1) and another (MS#12) at the outlet of LRW in 2001. At these stations, V-notch weirs
151 were installed, and the stage height of the water was recorded using a Campbell-
152 Scientific CR10X data logger. Stage height values were converted to total flow rates with
153 a calibration curve function (Chow et al., 2011). Water samples were collected with an
154 ISCO automatic sampler. Sampling frequency was set at one sample every 72 hours when
155 runoff was absent. During runoff events, sampling frequency was increased to one
156 sample every 5-cm change in stage height. Samples were analyzed for concentration of
157 suspended solids, nitrate-nitrogen (NO₃-N), and soluble-phosphorus (Sol-P). Detailed
158 description of data collection procedures and sample analyses can be found in Chow et al.
159 (2011). Weather data including daily precipitation, air temperature, relative humidity, and
160 wind speed were acquired from the St. Leonard Environment Canada weather station
161 (<http://climate.weather.gc.ca>), located approximately 5 km northwest of BBW (Fig. 1).
162 The daily average relative humidity and wind speed were calculated based on averaging

163 hourly values. Since this weather station did not monitor daily solar radiation, the study
164 used solar radiation collected from a weather station located approximately 10 km
165 southeast of BBW (WS#08; Fig. 1).

166 **2.2 SWAT Setup, Calibration, and Validation for BBW and LRW**

167 A modified version of SWAT has been developed for cold regions (Qi et al., 2017a;
168 Qi et al., 2016a; Qi et al., 2016b; Qi et al., 2017b), and it was used for BBW and LRW in
169 present study. Detailed model setup, calibration, and validation for BBW can be found in
170 Qi et al. (2017b). Specific model inputs for both watersheds are provided in Table 1. The
171 same weather data were used for both watersheds (Table 1). The Digital Elevation Model
172 (DEM) for LRW and BBW were both based on high resolution LiDAR (Light Detection
173 and Ranging) data, the first was created at 10-m and the second, at 1-m resolution. The
174 LRW was delineated into 32 subbasins from which their topographic characteristics were
175 defined (Fig. 1). The soil types and slopes, which were classified into five separate
176 classes, are illustrated in Fig. 2 for LRW. After combining the soil, slope, and land use
177 maps through the ArcSWAT-interface function, 362 HRUs were subsequently created for
178 LRW (based on thresholds: 10, 15, and 20% for land use, soil, and slope).

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186 **Table 1** Datasets in SWAT setup, calibration, and validation for BBW and LRW.

Dataset	BBW	LRW
LiDAR DEM resolution	1-m	10-m
Soil map	Survey (1993)	ERD
Land use maps	Survey (1992-2011)	ERD (one map)
Precipitation, temperature, relative humidity & wind speed	St. Leonard (1992- 2011)	St. Leonard (2001- 2010)
Solar radiation	WS#08 (1992-2011)	WS#08 (2001-2010)
Contour tillage operation (spring and fall)	Survey (1992-2011)	Only for potato and barley (2001-2010)
Fertilizer application	Survey (1992-2011)	Estimated from BBW (2001)
Crop rotation	Survey (1992-2011)	Potato-barley (2001- 2010)
Terraces and grassed waterways	Survey (1992-2011)	Negligible
Discharge, sediment, NO ₃ -N and Sol-P	MS#01 (1992-2011)	MS#12 (2001-2010)

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188 Since only one land use map was available for LRW (Table 1), assumptions were
 189 made based on information available on land use and management records for BBW to
 190 adjust the SWAT-management files for LRW as follows:

191 (1) Potato-barley rotations were assigned to the land use ID POTA (Table 2); for other
 192 land use IDs, a single crop was considered;

193 (2) Fertilizers were applied only to potato and barley fields, and fertilizer amounts and
 194 N:P (nitrogen-to-phosphorus) ratios were averaged for potato and barley fields over the
 195 entire watershed, based on 2001 survey data from BBW;

196 (3) Contour tillage was applied only to potato and barley fields;

197 (4) Flow diversion terraces (FDT) and grassed waterways in LRW were assumed not
 198 used. It is worth noting that these four assumptions serve as a baseline scenario for the
 199 assessment of FDT in LRW at a later time.

200 In order to evaluate the global performance of the decision support tool for LRW,
 201 related land use and management files were prepared and accessed by SWAT. For

202 purpose of comparison, simulations with SWAT were produced in an initial application
203 by setting the adjustable parameters of the model to their default values, and in a second
204 application by setting the parameters according to values produced with a watershed-
205 specific model calibration to BBW. This approach with model parameterization is widely
206 accepted when applying SWAT to large ungauged watersheds (Panagopoulos et al.,
207 2011).

208 **2.3 Decision Rules**

209 The decision support tool was designed to use the “decision rules” to estimate annual
210 discharge and sediment and nutrient loadings from individual grid cells:

$$211 \quad A = \sum_{i=1}^n DR_i \cdot A_i, \quad (1)$$

212 where A is the annual discharge or sediment and nutrient loadings at the outlet of the
213 watershed, DR_i and A_i are the delivery ratios and annual discharge or loadings,
214 respectively, for grid cell i . For the present study, statistical equations derived from
215 simulations of the calibrated version of SWAT-model for BBW were defined as the
216 “decision rules” in the decision support tool.

217 **2.3.1 Land Use Groups and BMP Scenarios**

218 In statistical equation development, land use in BBW (24, in total) was first classified
219 into five land use classes according to their influences on hydrological processes (Table
220 2). Note that WATR was not used due to its small overall coverage (Fig. 2). As for
221 watershed management, we considered three main BMPs, i.e.,

222 (1) FDT + contour tillage;

223 (2) Contour tillage; and

224 (3) No-BMP (without FDT and contour tillage).

225

226 **Table 2** Land use and land use groups (LUGP) for BBW and LRW.

LUGP	Land use ID in SWAT	Land use type
AGRL (General crops)	AGRL	Agricultural Land-Generic
	CANA	Canola
	CRON	Corn
	FPEA	Field peas
	POTA	Potato
GRAN (Grains)	BARL	Barley
	OATS	Oats
	PMIL	Millet
	RYE	Rye
	SWHT	Spring wheat
GRAS (Grasses)	WWHT	Winter wheat
	BERM	Bermuda grass
	CLVR	Clover
	HAY	Hay
	PAST	Past
	RYEG	Ryegrass
FORT (Forestry)	TIMO	Timothy
	FRSD	Forest-Deciduous
	FRSE	Forest-Evergreen
	FRST	Forest-Mixed
	RNGB	Range-Bush
	WETF	Wetlands-Forested
NOCR (Non-vegetated lands)	WETN*	Wetlands-No-Forest
	URMD	Residential
	UTRN	Transportation
	UIDU*	Industrial

Note: "*" indicates unique land use types to LRW not present in BBW and, therefore, unaccounted for in the development of the decision support tool.

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228 The calibrated version of the enhanced SWAT-model for BBW was used to generate

229 annual outputs based on HRUs from 1992 to 2011. The model was ran three times to

230 generate the BMP-specific data for statistical equation development.

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233 2.3.2 Explanatory Variables Selection

234 Explanatory candidate variables must be physically-meaningful in hydrological and
235 biochemical processes. It is worth noting that both continuous and categorical variables
236 were included in the regression equation. The land use group (LUGP) was the only
237 categorical variable, and the remaining were all continuous variables. To detect
238 significant predictors, the analysis of covariance (ANCOVA) was used. It requires at
239 least one continuous and one categorical explanatory variable and is used to identify the
240 major and interaction of predictor variables. By including continuous variables, the
241 method can reduce the variance of error to increase the statistical power and precision in
242 estimating categorical variables (Keselman et al., 1998; Li et al., 2014). Inclusion of
243 interaction terms in these regression models dramatically increased model performance.

244 In the present study, we only considered interactions between two explanatory variables
245 at a time. Student t-tests were conducted to examine the statistical significance of each
246 level of LUGP and their interaction with the various continuous variables. When one
247 level of LUGP (e.g., GRAN; Table 2) did not significantly correlate with water quality or
248 quantity, or there were nominal interactions between a given level and other explanatory
249 variables, this particular level of LUGP would be combined with other levels of LUGP
250 until all new levels of LUGP were statistically significant.

251 Multiple linear regression analyses were used to relate annual total discharge (mm) and
252 sediment ($t\ ha^{-1}$), NO_3-N ($kg\ ha^{-1}$), and Sol-P ($kg\ ha^{-1}$) loadings to the explanatory
253 variables. These work was conducted in R (Ihaka and Gentleman, 1996). Only six
254 continuous explanatory variables were determined for the specification of the statistical
255 models. Annual precipitation (PCP), annual mean air temperature (TMP), and mean

256 saturated hydraulic conductivity of soil (SOL_K) were common to the dependent
 257 variables (i.e., total discharge and sediment, NO₃-N, and Sol-P loadings). The LS-factor
 258 (USLE_LS) and annual N and P application rates (N_APP and P_APP) were unique to
 259 the equations addressing sediment, NO₃-N, and Sol-P loading.

260 **2.3.3 Delivery Ratio Definition**

261 The LS-factor of the universal soil loss equation (USLE) was determined by slope
 262 gradient (*slp*) and slope length (*L*) of individual HRUs:

$$263 \text{ USLE_LS} = \left\{ \frac{L}{22.1} \right\}^m \cdot (65.41 \cdot \sin^2(a) + 4.56 \cdot \sin(a) + 0.065) \quad (2)$$

264 where *m* is the equation exponent and *a* is the angle of the slope (in degrees). The
 265 exponent *m* is calculated by,

$$266 m = 0.6 \cdot (1 - \exp[-35.835 \cdot slp]) \quad (3)$$

267 where *slp* is in units of m m⁻¹. For the decision support tool, slope length *L* equals to the
 268 length of the grid side and slope gradient was determined by the *Slope* tool in ArcGIS.

269 The sediment-delivery ratio was not considered in the decision support tool application to
 270 BBW. We assumed that annual sediment loadings from grid cells in decision support tool
 271 were all exported to the outlet of BBW. However, when the decision support tool was
 272 applied to LRW, the sediment-delivery ratio was used to correct estimates of sediment
 273 loading at the watershed outlet. The sediment loadings at the outlet of LRW (*sed*) were
 274 determined by

$$275 sed = SDR \cdot sed^{\sim} \quad (4)$$

276 where *sed*[~] is the sediment loading calculated with the sediment loading equation (one for
 277 each BMP and land use group), and *SDR* is determined by (Vanoni, 1975)

$$278 SDR = 0.37 \cdot D^{-0.125} \quad (5)$$

279 where D (km^2) is the drainage area. For annual discharge and nutrient loadings, we
280 assumed their delivery ratios equal to 1.0 for all grid cells in LRW.

281 **2.4 Decision Support Tool Assessment**

282 Inputs to the decision support tool included the six continuous explanatory variables
283 and LUGP as well as information on management practices, e.g., contour tillage and FDT
284 implementation. Simulations from each grid cells were summarized at the outlet of the
285 study watersheds. We first tested the impact of cell size on simulations of water quantity
286 and quality at the outlet of BBW. The cell size range was determined by considering
287 different farmland sizes in the watershed. We assumed that farmland-based grid cells can
288 sufficiently represent basic hydrological processes, land use change, and management
289 practice implementations for hydrological modeling. Simulated annual water flow and
290 sediment and nutrient loadings with the decision support tool were compared with those
291 produced with the calibrated version of the enhanced SWAT-model. Subsequently, the
292 decision support tool was applied to LRW, and the simulations were compared with the
293 results of the uncalibrated and calibrated versions of SWAT. The purpose of this was to
294 test if the decision support tool (i.e., land use and BMP assessment tool; LBAT)
295 performed better, or at least as well, as both the uncalibrated and calibrated version of
296 SWAT.

297 Model performance in terms of water quantity and quality at the outlet of the study
298 watersheds was assessed based on the coefficient of determination (R^2) and relative error
299 (Re), i.e.,

$$300 \quad R^2 = \left(\frac{\sum_{i=1}^n (O_i - O_{avg}) \cdot (P_i - P_{avg})}{\left[\sum_{i=1}^n (O_i - O_{avg})^2 \cdot \sum_{i=1}^n (P_i - P_{avg})^2 \right]^{0.5}} \right)^2 \quad (6)$$

301
$$Re = \frac{(P_{avg} - O_{avg})}{O_{avg}} \cdot 100\% \quad (7)$$

302 where O_i , P_i , O_{avg} , and P_{avg} are the observed and predicted and averages of the observed
 303 and predicted values, respectively.

304

305 **2.5 FDT Assessment in LRW**

306 A series of FDT-implementation scenarios were set up for LBAT based on six slope
 307 classes to assess the impact of FDT on water quantity and quality on agricultural lands in
 308 LRW (Fig. 3; Table 3). From scenarios one (S1) to six (S6), total area protected by FDT
 309 gradually increased until all agricultural lands were protected (Table 3). Mean annual
 310 simulations of total discharge and sediment, NO₃-N, and Sol-P loadings from LRW from
 311 2001 to 2010 were compared with those of the baseline scenario (FDT = 0%) for each
 312 scenario using two performance indicators, i.e., mean difference (MD) and % relative
 313 difference (PRD), given as:

314 (1) MD = output with FDT – output without FDT, and

315 (2) PRD (%) = MD/output without FDT × 100.

316

317 **Table 3** Slope classes and corresponding areas in the agricultural land of LRW.

Scenario	Slope	Area protected by FDT	Agricultural lands
		(ha)	(%)
S1	≥5%	624	10
S2	≥4%	1328	22
S3	≥3%	2224	37
S4	≥2%	3680	61
S5	≥1%	5360	89
S6	≥0	6048	100

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320 **3. Results and Discussion**

321 **3.1 Statistical Equations (Decision Rules)**

322 **3.1.1 Model Structure and Coefficients**

323 Linear regression equations and their explanatory variables for annual discharge and
324 sediment, NO₃-N, and Sol-P loadings under different combinations of land use groups
325 and BMP scenarios are provided in Tables 4 and 5. In total, three discharge models (Dis1,
326 Dis2, and Dis3) and five sediment (Sed1_1, Sed1_2, Sed1_3, Sed2, and Sed3), NO₃-N
327 (N1_1, N1_2, N1_3, N2, and N3), and Sol-P (P1_1, P1_2, P1_3, P2, and P3) loading
328 models were developed. Data transformations (via logarithm and power transformations)
329 were applied to sediment, NO₃-N, and Sol-P loadings to meet the assumption of
330 normality in multiple regression analysis (Table 4). The contour tillage and FDT were
331 applied only to agricultural lands, including land use groups AGRL, GRAN, and GRAS
332 (Table 4). For the no-BMP scenario, three separate sediment, NO₃-N, and Sol-P loading
333 models were developed for agricultural lands (AGRL, GRAN, and GRAS), non-
334 vegetated lands (NOCR), and forest lands (FORT), and one discharge model (Dis1) for
335 all land use groups (Table 4). It is worth noting that the sediment loading model, Sed3,
336 was a modified version of Sed1_1 (multiplied by TERR_P) for the FDT + contour tillage
337 scenario (Table 4), and the values of TERR_P (Qi et al., 2017b) used for Sed3 were the
338 same as the calibrated values in SWAT for BBW (Qi et al., 2017b). Also, NO₃-N and
339 Sol-P loadings (N1_2 and P1_2) for non-vegetated lands (NOCR) were determined as
340 constants, which were equal to the calculated means of NO₃-N and Sol-P loadings
341 determined by SWAT (i.e., 24 and 0.61 kg ha⁻¹, respectively; Table 4).

342 As for LUGP (including AGRL, GRAN, GRAS, FORT, and NOCR; Table 2), three
343 new land use groups (i.e., LUGP1, LUGP2, and LUGP3) were formulated by combining
344 agricultural lands AGRL, GRAN, and GRAS during model development (Tables 4 and 5).
345 For example, LUGP2 was derived by combining AGRL, GRAN, and GRAS on total
346 discharge (i.e., Dis1 model). Individual model structures are shown in Table 4, whereas
347 the explanatory variables for these models appear in Appendix. The coefficients
348 estimated for the explanatory variables and their interactions, and their t-test results are
349 also shown in Appendix. Most of the *p*-values for these explanatory variables were <
350 0.001, except for several that were between 0.001 and 0.08, which were also taken as
351 acceptable.

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Table 4 Statistical models based on land use groups (LUGP) and BMPs.

BMPs	LUGP*	Model	Structure
No-BMP	CRGP2,NOCR,FORT	Dis1	Discharge = $f(\text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP2})$
Contour tillage	AGRL,GRAN,GRAS	Dis2	= $f(\text{PCP}, \text{TMP}, \text{SOL_K})$
FDT+Contour tillage	AGRL,GRAN,GRAS	Dis3	= $f(\text{PCP}, \text{TMP}, \text{SOL_K})$
No-BMP	CRGP1,GRAS	Sed1_1	Sediment ^(1/10) = $f(\text{USLE_LS}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP1})$
	NOCR	Sed1_2	= $f(\text{USLE_LS}, \text{PCP})$
	FORT	Sed1_3	= $f(\text{USLE_LS}, \text{PCP}, \text{SOL_K})$
Contour tillage	CRGP1,GRAS	Sed2	Sediment ^(1/10) = $f(\text{USLE_LS}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP1})$
FDT+Contour tillage	AGRL,GRAN,GRAS	Sed3	Sediment = Sed1_1 × TERR_P
No-BMP	AGRL,GRAN,GRAS	N1_1	Log(NO ₃ -N) = $f(\text{N_APP}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP})$
	NOCR	N1_2**	NO ₃ -N = 24 kg ha ⁻¹
	FORT	N1_3	Log(NO ₃ -N) = $f(\text{PCP}, \text{TMP}, \text{SOL_K})$
Contour tillage	AGRL,GRAN,GRAS	N2	Log(NO ₃ -N) = $f(\text{N_APP}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP})$
FDT+Contour tillage	CRGP3,GRAN	N3	= $f(\text{N_APP}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP3})$
No-BMP	CRGP1,GRAS	P1_1	Log(Sol-P) = $f(\text{P_APP}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP1})$
	NOCR	P1_2**	Sol-P = 0.61 kg ha ⁻¹
	FORT	P1_3	Log(Sol-P) = $f(\text{PCP}, \text{TMP}, \text{SOL_K})$
Contour tillage	CRGP1,GRAS	P2	Log(Sol-P) = $f(\text{P_APP}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP1})$
FDT+Contour tillage	AGRL,GRAN,GRAS	P3	= $f(\text{P_APP}, \text{PCP}, \text{TMP}, \text{SOL_K}, \text{LUGP})$

356

*AGRL and GRAN are combined into one group, namely CRGP1 in LUGP1; AGRL, GRAN and GRAS are combined into one group, namely

357

CRGP2 in LUGP2; AGRL and GRAS are combined into one group, namely CRGP3 in LUGP3; ** variable is set constant.

Table 5 Explanatory variables determined for statistical analysis.

Variable	Unit	Meaning
LUGP	—	Land use groups including AGRL, GRAN, GRAS, FORT, and NOCR
LUGP1	—	AGRL and GRAN are combined into a new group, CRGP1
LUGP2	—	AGRL, GRAN, and GRAS are combined into a new group, CRGP2
LUGP3	—	AGRL and GRAS are combined into a new group, CRGP3
N_APP	kg ha ⁻¹	Annual N application rate
P_APP	kg ha ⁻¹	Annual P application rate
PCP	mm	Annual precipitation
SOL_K	mm h ⁻¹	Mean saturated hydraulic conductivity of soil
TERR_P	—	P-factor for FDT
TMP	°C	Annual mean air temperature
USLE_LS	—	LS-factor of USLE

359

360 3.1.2 Statistical Equation Assessment

361 Simulations based on the statistical equations and the calculated outputs from
 362 individual HRUs for the different BMPs are compared in Table 6. In general, discharge
 363 models were able to reproduce SWAT simulations for the three BMPs; R^2 ranging from
 364 0.86 to 0.9. Mean discharge simulated with the statistical equations was equal to that of
 365 SWAT (Table 6). Mean discharge (636 mm) for the no-BMP-case (BMP 3) was greater
 366 than that for BMPs using contour tillage and FDTs (619 and 628 mm for BMP 1 and 2,
 367 respectively), suggesting that contour tillage and FDTs can cause evapotranspiration to
 368 increase.

369 Models Sed1_2 and Sed1_3 were able to reproduce simulations with SWAT (yielding
 370 $R^2 = 0.71$ and 0.57 , respectively), and simulated mean sediment loadings were close to
 371 that of SWAT (Table 6). Models Sed1_1 and Sed2 tended to underestimate results from
 372 SWAT (Table 6), with an overall lower mean sediment loading of 10.78 vs. 12.84 and
 373 8.31 vs. 9.4 t ha⁻¹, respectively. Mean sediment loading with Sed3 (0.89 t ha⁻¹) was
 374 slightly greater than that of SWAT (0.84 t ha⁻¹), due to the fact that Sed3 only took into

375 account TERR_P, whereas SWAT took into account TERR_CN and the impact of
376 grassed waterways. Results from the statistical equations showed that the mean sediment
377 loading for BMP 2 (8.31 t ha⁻¹) was significantly different than that for BMPs 1 and 3,
378 with mean loading of 0.89 and 10.78 t ha⁻¹ (Table 6). The smallest mean sediment
379 loading (0.09 t ha⁻¹) was found to occur with the FORT land use grouping (Table 6).

380 The four NO₃-N and Sol-P loading equations explained ~50% of the variation in the
381 SWAT simulations for the same variables, with R² ranging from 0.33 to 0.59 (Table 6).
382 Mean NO₃-N and Sol-P loadings with the statistical equations were all slightly less than
383 the values produced with SWAT for the different BMPs (Table 6). Mean NO₃-N loadings
384 were greater for BMP 1 (44 kg ha⁻¹) than those for BMPs 2 and 3 with both giving 39 kg
385 ha⁻¹ (Table 6), due to increased infiltration with FDT. Mean Sol-P loading (0.8 kg ha⁻¹)
386 was less for BMP 3 than for BMP 2 (0.89 kg ha⁻¹), whereas much greater than for BMP 1
387 (0.43 kg ha⁻¹). Although contour tillage can help reduce sediment loading by modifying
388 micro-topography and reducing erosion runoff (the reason we set USLE_P < 1), Sol-P
389 transported with surface runoff increased due to reduced residue cover protecting the soil
390 surface during winter and during the snowmelt season. When FDT was implemented with
391 tillage, however, less surface runoff was generated due to increased infiltration leading to
392 a reduction in Sol-P loading. Mean NO₃-N and Sol-P loadings for the FORT land
393 grouping (10 vs. 0.06 kg ha⁻¹) were much less than those of the CRGP land grouping, 39
394 vs. 0.8 kg ha⁻¹ (Table 6).

395 **Table 6** Comparisons of simulations of statistical models and outputs from SWAT for different land use groups and BMPs based on
 396 mean and standard deviation for the entire simulation period (1992-2011).

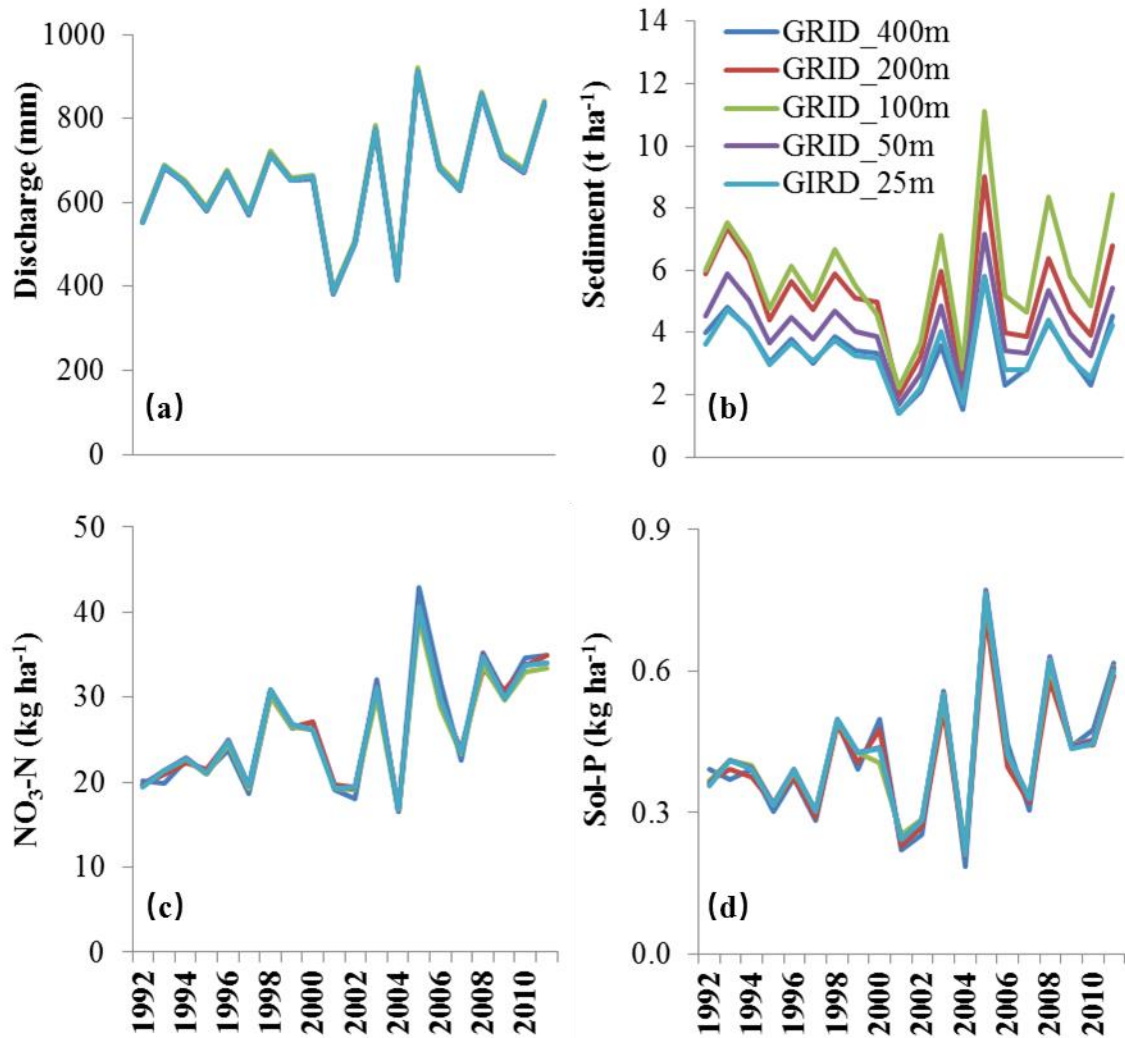
Variable	Index	No-BMP						Tillage		FDT + Tillage	
		CRGP		NOCR		FORT		CRGP		CRGP	
		SWAT	Fitted	SWAT	Fitted	SWAT	Fitted	SWAT	Fitted	SWAT	Fitted
Discharge (mm)	Mean	→	→	636	636	←	←	619	619	628	628
	SD	→	→	144	133	←	←	140	132	151	143
	R ²	→	→	0.86 (Dis1)		←	←	0.88 (Dis2)		0.90 (Dis3)	
Sediment (t ha ⁻¹)	Mean	12.84	10.78	1.80	1.71	0.10	0.09	9.40	8.31	0.84	0.89
	SD	11.86	9.44	1.94	1.95	0.14	0.16	8.28	7.38	2.72	1.18
	R ²	0.48 (Sed1_1)		0.71 (Sed1_2)		0.57 (Sed1_3)		0.56 (Sed2)		—	
NO ₃ -N (kg ha ⁻¹)	Mean	43	39	24	—	10	10	43	39	47	44
	SD	24	14	16	—	6	3	24	14	29	21
	R ²	0.40 (N1_1)		—		0.33 (N1_3)		0.39 (N2)		0.59 (N3)	
Sol-P (kg ha ⁻¹)	Mean	0.88	0.80	0.61	—	0.08	0.06	0.98	0.89	0.49	0.43
	SD	0.49	0.32	0.46	—	0.06	0.03	0.59	0.38	0.33	0.23
	R ²	0.47 (P1_1)		—		0.38 (P1_3)		0.48 (P2)		0.52 (P3)	

397 Note: CRGP refers to crop groups including AGRL, GRAN, and GRAS; the statistics for discharge in no-BMP scenario are
 398 based on CRGP, NOCR, and FORT.

399 3.2 LBAT Assessment

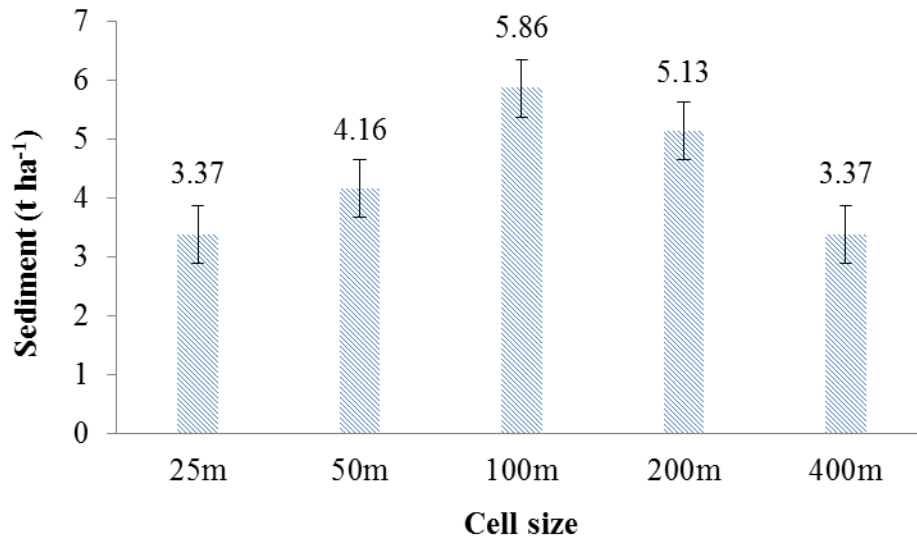
400 3.2.1 Impact of Grid Cell Size on LBAT Simulation

401 Simulations of water quantity and quality by LBAT with different grid-cell sizes (i.e.,
402 25, 50, 100, 200, and 400 m) for BBW are shown in Fig. 3. Statistical tests indicated that
403 grid-cell size had a significant effect on sediment loading (p -value < 0.01), with no effect
404 observed for discharge and $\text{NO}_3\text{-N}$ and Sol-P loadings (p -values > 0.99). Increasing cell
405 size (i.e., slope length) increased sediment loading. However, the mean slope gradient
406 was reduced. As a result, the mean sediment loadings were correlated non-linearly with
407 cell size as shown in Fig. 4. The highest mean sediment loading was found with a cell
408 size of 100 m (5.86 t ha^{-1}), whereas the lowest was found to occur with a cell size of 25
409 and 400 m (3.37 t ha^{-1}). The LBAT with a cell size of 25 and 400 m was able to generate
410 sediment loadings consistent with field measurements. Considering computational
411 efficiency, we chose a grid-cell size of 400 m as the basic LBAT-simulation unit for
412 LRW.



413

414 **Fig. 3** LBAT-produced simulations of annual stream discharge and sediment, NO₃-N, and
 415 Sol-P loadings determined for different DEM grid-cell sizes (i.e., 25, 50, 100, 200, and
 416 400 m).



417

418 **Fig. 4** Impact of grid-cell size on LBAT-simulation of sediment loading. Mean annual
419 sediment loadings and standard errors (vertical bars) from 1992 to 2011 are indicated.

420 3.2.2 LBAT vs. SWAT in LRW

421 Simulations of water quantity and quality with LBAT and the uncalibrated and
422 calibrated versions of SWAT are compared with field measurements for LRW (Fig. 5).
423 Model assessments for different simulation periods (depending on measurement
424 availability) are shown in Table 7. It is worth noting that, to eliminate unrealistic results,
425 USLE_LS was constrained in Sed1_2 to the NOCR land use group:

$$426 \text{USLE_LS} = \begin{cases} \text{Eq. 6-1} & \text{USLE_LS} \leq 1.28 \\ 1.28 & \text{USLE_LS} > 1.28 \end{cases} \quad (8)$$

427 where 1.28 is the maximum USLE_LS for BBW.

428 In general, the two versions of SWAT and LBAT slightly underestimated annual
429 stream discharge, capturing its variation reasonably well ($R^2 > 0.54$; Fig. 5a). The
430 uncalibrated and calibrated versions of SWAT had the least and largest absolute values of
431 Re (Re = -2 and -9), whereas LBAT Re = -6 (Table 7). The uncalibrated version of
432 SWAT severely overestimated annual sediment and NO₃-N loading (Re = 212 and 87,
433 respectively; Figs. 5b and c), whereas the calibrated version of SWAT and LBAT
434 underestimated sediment loading (Re = -32 and -52, respectively) and overestimated
435 NO₃-N loading (Re = 22 and 27, respectively; Table 7). In general, the calibrated version
436 of SWAT and LBAT captured the variation in annual NO₃-N loadings reasonably well
437 ($R^2 > 0.35$; Fig. 5c). However, the two versions of SWAT and LBAT failed to capture the
438 variation in annual sediment and Sol-P loadings (low R^2 ; Figs. 5b and d). The LBAT had
439 the smallest absolute value of Re (i.e., Re = -16), while the uncalibrated and calibrated
440 versions of SWAT had larger values (Re = -59 and -55, respectively). These results
441 suggested that the LBAT and the calibrated version of SWAT performed fairly
442 equivalently in simulating annual stream flow and sediment and NO₃-N loadings, with

443 LBAT performing slightly better for annual Sol-P loading. LBAT performed noticeably
 444 better than the uncalibrated version of SWAT, especially for annual sediment and NO₃-N
 445 loadings. Poor performance for both versions of SWAT and LBAT on simulation of
 446 annual sediment and Sol-P loadings in LRW might attribute to lack of detailed
 447 management practice and fertilizer application information from agricultural lands. We
 448 only had one year data for LRW and made assumptions about rotation and management
 449 practices for other years based on information from BBW, which could introduce major
 450 input uncertainty.

451

452 **Table 7** Statistical assessments of LBAT and SWAT for annual stream discharge and
 453 sediment, NO₃-N, and Sol-P loadings at the outlet of LRW for different simulation
 454 periods

Period	Variable	Index	Measurement	SWAT -Uncalibrated	SWAT -Calibrated	⁴⁵⁵ LBAT
01-07	Discharge (mm)	Mean	704	691	638	456
		Re (%)	—	-2	-9	-6
		R ²	—	0.63	0.69	0.57
01-10	Sediment (t ha ⁻¹)	Mean	0.95	2.95	0.65	0.45
		Re (%)	—	212	-32	458
		R ²	—	0.01	0.01	0.04
03-10	NO ₃ -N (kg ha ⁻¹)	Mean	12	22	14	15
		Re (%)	—	87	22	460
		R ²	—	0.59	0.45	0.35
03-10	Sol-P (kg ha ⁻¹)	Mean	0.31	0.13	0.14	0.26
		Re (%)	—	-59	-55	-16
		R ²	—	0.02	0.11	0.01

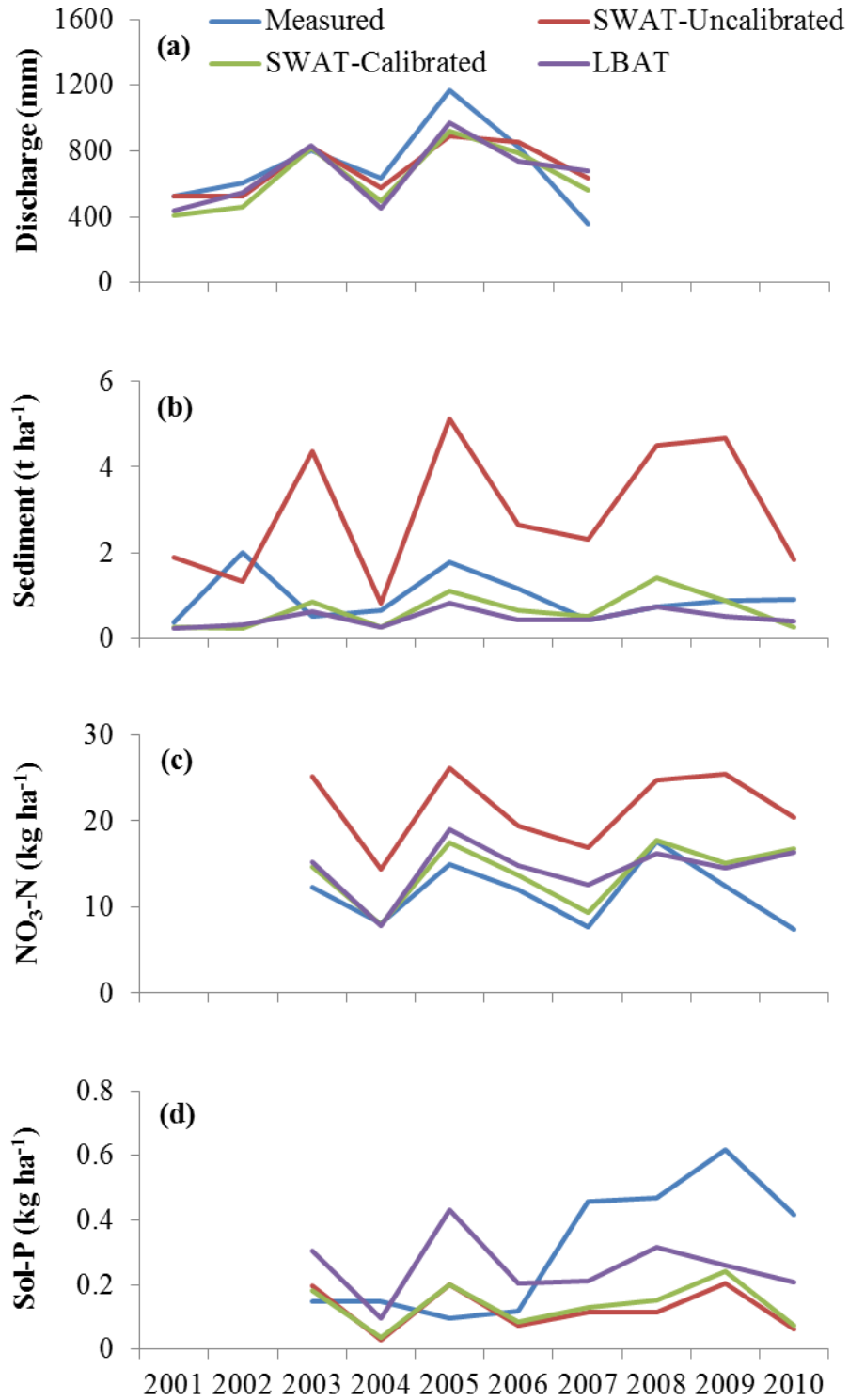
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467 Since LBAT is based on decision rules (statistical equations in this study) which
468 were derived from SWAT simulations for BBW, its usage should be constrained to areas
469 with soil, landscape, and land use characteristics similar to BBW. Input characteristics
470 exceeding the range of SWAT data considered could lead to large errors in predictions.
471 LBAT is flexible in its structure, and with thoughtful development of internal rules, it can
472 be applied to diverse environments.



473

474 **Fig. 5** Simulations of annual stream discharge and sediment, NO₃-N, and Sol-P loadings

475 with LBAT and SWAT compared with field measurements at the outlet of LRW.

476

477 **3.2.3 FDT Assessment in LRW**

478 Mean annual water quantity and quality simulated with LBAT for agricultural lands of
479 LRW are shown in Table 8. The mean annual discharge for the baseline scenario was 626
480 mm greater than that for the six FDT scenarios (Table 8). When all agricultural lands
481 were protected (S6), there was a 2% reduction in discharge (equivalent to 11 mm; Table
482 8). With the steepest areas protected (accounting for 10% of the total land base; S1), the
483 mean annual sediment loading was reduced by as much as 43% (equivalent to 4.5 t ha⁻¹;
484 Table 8) and by as much as 81% (i.e., 8.57 t ha⁻¹) with all agricultural lands protected (S6;
485 Table 8). Mean annual Sol-P loading was reduced by 51% (equivalent to 0.47 kg ha⁻¹;
486 Table 8). In contrast, increased usage of FDT tended to increase the mean annual loading
487 of NO₃-N, by about 6% when used across all agricultural lands (equivalent to 1.73 kg ha⁻¹;
488 ¹).

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498 **Table 8** Impact of FDT on mean annual discharge and sediment, NO₃-N, and Sol-P
 499 loadings simulated with LBAT under different FDT, provided in Table 3.

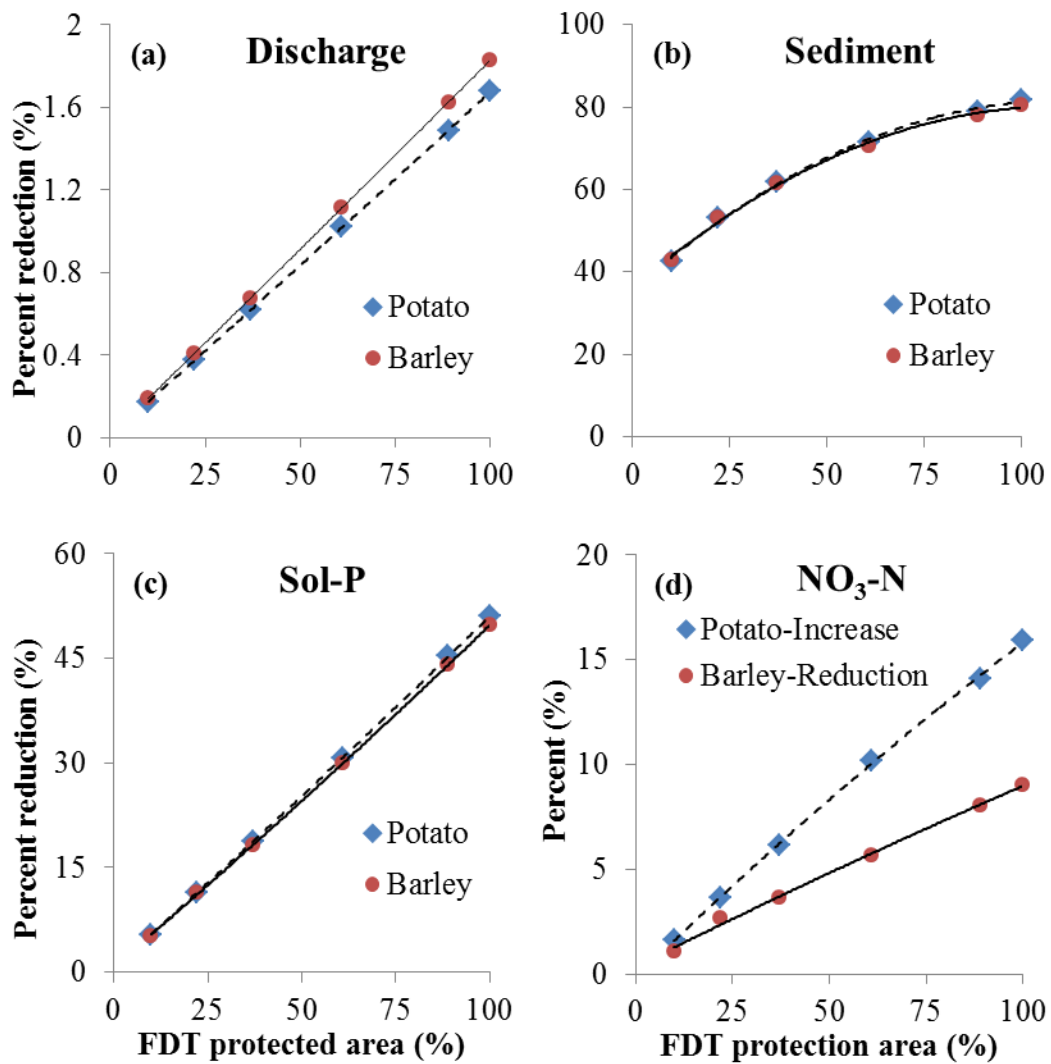
Variable	Index	Baseline	S1	S2	S3	S4	S5	S6
Discharge (mm)	Mean	626	625	623	622	619	616	615
	MD	—	-1	-2	-4	-7	-10	-11
	PRD (%)	—	0	0	-1	-1	-2	-2
Sediment (t ha ⁻¹)	Mean	10.54	6.04	4.94	4.02	3.04	2.26	1.97
	MD	—	-4.50	-5.60	-6.52	-7.50	-8.28	-8.57
	PRD (%)	—	-43	-53	-62	-71	-79	-81
NO ₃ -N (kg ha ⁻¹)	Mean	29.70	29.86	30.02	30.34	30.82	31.22	31.42
	MD	—	0.16	0.32	0.64	1.13	1.52	1.73
	PRD (%)	—	1	1	2	4	5	6
Sol-P (kg ha ⁻¹)	Mean	0.94	0.89	0.83	0.76	0.65	0.52	0.46
	MD	—	-0.05	-0.11	-0.17	-0.28	-0.42	-0.47
	PRD (%)	—	-5	-11	-19	-30	-45	-51

500

501 Percentage change (based on PRD) of water quantity and quality were plotted against
 502 percentage area of FDT for potato and barley in Fig. 6. Increasing the usage of FDT
 503 helped to reduce discharge and sediment and Sol-P loadings for both crop types (Figs. 6a,
 504 b, and c). It is worth noting that sediment loading decreased with increasing usage of
 505 FDT (Fig. 6b). An opposite trend was observed for potato and barley with respect to the
 506 impact of FDT on NO₃-N loading. With the increased usage of FDT, NO₃-N loadings
 507 increased linearly for potato, while it decreased for barley. The increased for potato was
 508 nearly twice as much as the reduction for barley (Fig. 6d). Seemingly the interaction
 509 between barley and FDT had positive impacts on nitrate retention in soils, whereas the
 510 interaction between potato and FDT had an opposite effect.

511 These results are consistent with the results from previous studies (Yang et al., 2012;
 512 Yang et al., 2010), which used SWAT to assess the impact of FDT on water quantity and
 513 quality within BBW. When using SWAT, greater efforts are needed to prepare basic

514 inputs, such as daily weather records, to proceed with its calibration and validation,
 515 involving complex scenario setup and analysis. For every new watershed, SWAT needs
 516 dedicated effort and time for its setup. LBAT, in contrast, can be used for multiple
 517 watersheds as long as they have similar environmental conditions. Scenario analysis can
 518 be directly conducted with different combinations of land use and BMPs using fewer
 519 inputs than what is required by SWAT. Also, once developed, LBAT does not require
 520 additional calibration.



521

522 **Fig. 6** Percentage change in discharge and sediment, NO₃-N, and Sol-P loadings as a
 523 function of % area, where FDT's were used.

524 **4. Conclusion**

525 The present study addresses the development of a decision support tool to assess the
526 impact of land use change and BMPs on water quantity and quality for ungauged
527 watersheds. An enhanced version of SWAT was calibrated and validated for an small
528 experimental watershed. Multiple regression analyses were used to develop statistical
529 equations based on simulations from SWAT. In total, three discharge and five sediment,
530 NO₃-N, and Sol-P loading models were developed for different combinations of land use
531 groups and BMP scenarios. Only four common predictors (i.e., annual precipitation,
532 annual mean air temperature, mean saturated hydraulic conductivity of soil, and land use
533 groups) and three unique predictors (LS-factor and annual nitrogen and phosphorus
534 application rates for sediment, NO₃-N, and Sol-P loading models, respectively) are
535 required.

536 With the aid of ArcGIS, statistical equations were integrated into the decision support
537 tool, i.e., the land use and BMPs assessment tool (LBAT), whose basic simulation units
538 are the DEM-grid cell. The LBAT was used to simulate annual water flow and sediment
539 and nutrient loadings at the outlet of a larger watershed, i.e., Little River Watershed
540 (LRW). These simulations were compared with those of SWAT. Results indicated that
541 LBAT and the calibrated version of SWAT performed equivalently with respect to annual
542 stream discharge and sediment and NO₃-N loadings. LBAT performed slightly better,
543 when Sol-P loading was considered. Compared with the uncalibrated version of SWAT,
544 LBAT performed better. The impact of FDT on water quantity and quality was evaluated
545 with LBAT for LRW; its results were consistent with the results generated with SWAT
546 for the same region in previous studies. LBAT has fewer input requirements than SWAT,

547 and can be applied to multiple watersheds without additional calibration. Also, scenario
548 analyses can be directly conducted with LBAT without complex setup procedures. We
549 recommend using LBAT for economic analysis and management decision making for
550 watersheds with similar environmental conditions of New Brunswick. The LBAT
551 developed in this study may not be directly applied to other regions; however, the
552 approach in developing LBAT can be applied to other regions of the world because of its
553 flexible structure.

554

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570 **Appendix**

571 **Table 1** Coefficient values for the three discharge models.

Model variable	Estimate	Std. Error	t-value	p-value
Dis1				
Intercept	-1565	24.04	-65.089	<0.001
PCP	1.933	0.02176	88.837	<0.001
TMP	282.7	6.091	46.402	<0.001
SOL_K	0.06338	0.00992	6.389	<0.001
FORT	30.79	14.16	2.175	0.030
NOCR	162.2	14.51	11.181	<0.001
PCP:TMP	-0.2488	0.005487	-45.352	<0.001
PCP:FORT	0.04684	0.01191	3.934	<0.001
PCP:NOCR	-0.0535	0.01224	-4.37	<0.001
TMP:FORT	9.723	1.684	5.775	<0.001
TMP:NOCR	4.506	1.731	2.603	0.009
SOL_K:FORT	-0.3769	0.03403	-11.076	<0.001
SOL_K:NOCR	-0.2959	0.032	-9.248	<0.001
Dis2				
Intercept	-1633	27.29	-59.84	<0.001
PCP	1.995	0.02472	80.69	<0.001
TMP	302.2	6.87	43.98	<0.001
SOL_K	0.08696	0.01167	7.45	<0.001
PCP:TMP	-0.2662	0.006199	-42.94	<0.001
Dis3				
Intercept	-1666	36.58	-45.54	<0.001
PCP	2.007	0.03305	60.713	<0.001
TMP	298	9.351	31.865	<0.001
SOL_K	0.09353	0.01573	5.946	<0.001
PCP:TMP	-0.2606	0.008406	-31.004	<0.001

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Table 2 Coefficient values for the four sediment loading models.

Model variable	Estimate	Std. Error	t-value	p-value
Sed1_1				
Intercept	0.2749	0.06125	4.488	<0.001
USLE_LS	0.1201	0.02224	54.018	<0.001
PCP	0.000788	5.54E-05	14.218	<0.001
TMP	0.1117	0.01528	7.307	<0.001
SOL_K	0.000568	0.00022	2.585	0.010
GRAS	-0.0353	0.00881	-4.007	<0.001
USLE_LS:SOL_K	-0.00014	4.69E-05	-3.045	0.002
USLE_LS:GRAS	-0.02623	0.006826	-3.842	<0.001
PCP:TMP	-0.00011	1.38E-05	-7.967	<0.001
PCP:SOL_K	-4.6E-07	1.91E-07	-2.406	0.016
Sed1_2				
Intercept	0.8575	0.008826	97.15	<0.001
PCP	0.000123	7.82E-06	15.67	<0.001
PCP:USLE_LS	0.000209	5.02E-06	41.65	<0.001
Sed1_3				
(Intercept)	0.3992	0.02267	17.613	<0.001
USLE_LS	0.07935	0.01967	4.034	<0.001
PCP	0.000204	1.96E-05	10.371	<0.001
SOL_K	0.000545	5.71E-05	9.534	<0.001
USLE_LS:PCP	4.94E-05	1.71E-05	2.9	0.004
USLE_LS:SOL_K	-0.00067	4.89E-05	-13.718	<0.001
Sed2				
Intercept	0.2591	0.05228	4.956	<0.001
USLE_LS	0.12	0.001898	63.218	<0.001
PCP	0.000767	4.73E-05	16.212	<0.001
TMP	0.1162	0.01304	8.907	<0.001
SOL_K	0.000746	0.000188	3.981	<0.001
GRAS	-0.06937	0.01648	-4.211	<0.001
USLE_LS:SOL_K	-0.00013	4E-05	-3.137	0.002
USLE_LS:GRAS	-0.02662	0.005829	-4.567	<0.001
PCP:TMP	-0.00011	1.18E-05	-9.522	<0.001
PCP:SOL_K	-6.3E-07	1.63E-07	-3.846	<0.001
TMP:GRAS	0.007415	0.003664	2.024	0.043

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581

582

583 **Table 3** Coefficient values for the four NO₃-N loading models corresponding to land use
 584 and BMPs described in Table 4.

Model variable	Estimate	Std. Error	t-value	p-value
N1_1				
Intercept	1.44	0.1753	8.213	<0.001
N_APP	-0.00862	0.000699	-12.325	<0.001
PCP	0.000543	0.00016	3.4	<0.001
TMP	0.1363	0.03357	4.059	<0.001
SOL_K	-0.00344	9.78E-05	-35.163	<0.001
GRAN	-1.117	0.1021	-10.937	<0.001
GRAS	-1.97	0.1562	-12.611	<0.001
N_APP:PCP	5.31E-06	6.45E-07	8.233	<0.001
N_APP:TMP	0.000963	7.45E-05	12.929	<0.001
N_APP:SOL_K	9.6E-06	6.4E-07	15.024	<0.001
PCP:GRAN	0.000677	9.38E-05	7.215	<0.001
PCP:GRAS	0.001029	0.000143	7.201	<0.001
PCP:TMP	-0.00025	2.64E-05	-9.467	<0.001
TMP:GRAN	0.1	0.01134	8.817	<0.001
TMP:GRAS	0.2132	0.01651	12.912	<0.001
N1_3				
Intercept	-1.411	0.3087	-4.573	<0.001
PCP	0.001875	0.000279	6.710	<0.001
TMP	0.4437	0.07831	5.666	<0.001
SOL_K	-0.00104	0.000116	-8.979	<0.001
PCP:TMP	-0.00032	7.06E-05	-4.484	<0.001
N2				
Intercept	1.429	0.1757	8.134	<0.001
N_APP	-0.00858	0.000701	-12.233	<0.001
PCP	0.000548	0.00016	3.425	<0.001
TMP	0.1376	0.03365	4.089	<0.001
SOL_K	-0.00345	9.8E-05	-35.223	<0.001
GRAN	-1.11	0.1023	-10.849	<0.001
GRAS	-1.962	0.1566	-12.526	<0.001
N_APP:PCP	5.3E-06	6.47E-07	8.187	<0.001
N_APP:TMP	0.000957	7.46E-05	12.82	<0.001
N_APP:SOL_K	9.65E-06	6.4E-07	15.067	<0.001
PCP:GRAN	0.000674	9.41E-05	7.167	<0.001
PCP:GRAS	0.001026	0.000143	7.162	<0.001
PCP:TMP	-0.00025	2.64E-05	-9.456	<0.001
TMP:GRAN	0.09934	0.01137	8.738	<0.001
TMP:GRAS	0.2122	0.01655	12.821	<0.001

N3				
Intercept	-0.3595	0.1718	-2.092	0.037
N_APP	-0.00131	0.000435	-3.011	0.003
PCP	0.001621	0.00015	10.806	<0.001
TMP	0.3977	0.03857	10.312	<0.001
SOL_K	-0.00386	0.000505	-7.641	<0.001
GRAN	-0.2133	0.07504	-2.842	0.005
N_APP:PCP	1.65E-06	3.59E-07	4.61	<0.001
N_APP:TMP	0.000281	4.74E-05	5.939	<0.001
N_APP:GRAN	0.000716	0.000292	2.453	0.014
PCP:TMP	-0.00035	3.32E-05	-10.506	<0.001
PCP:SOL_K	1.21E-06	4.36E-07	2.781	0.005
PCP:GRAN	0.000267	5.82E-05	4.577	<0.001
TMP:GRAN	-0.04685	0.008004	-5.853	<0.001

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Table 4 Coefficient values for four Sol-P models.

Model variable	Estimate	Std. Error	t-value	p-value
P1_1				
Intercept	-3.711	0.1306	-28.416	<0.001
P_APP	0.002341	0.000623	3.757	<0.001
PCP	0.003195	0.000117	27.286	<0.001
TMP	0.5542	0.03197	17.337	<0.001
SOL_K	0.00298	0.000472	6.305	<0.001
GRAS	-0.4321	0.0382	-11.312	<0.001
P_APP:PCP	-2.4E-06	5.2E-07	-4.64	<0.001
P_APP:TMP	0.000829	7.7E-05	10.797	<0.001
PCP:TMP	-0.00052	2.9E-05	-18.297	<0.001
PCP:SOL_K	-1.2E-06	3.97E-07	-3.095	0.002
TMP:SOL_K	-0.00026	5.7E-05	-4.526	<0.001
TMP:GRAS	0.03787	0.00941	4.024	<0.001
P1_3				
Intercept	-4.43817	0.589848	-7.512	<0.001
PCP	0.002509	0.000534	4.701	<0.001
TMP	0.417306	0.1496445	2.789	0.005
SOL_K	0.001247	0.000222	5.622	<0.001
PCP:TMP	-0.0003	0.000135	-2.253	0.024
P2				
Intercept	-3.667	0.1357	-27.017	<0.001
P_APP	0.003461	0.000663	5.218	<0.001
PCP	0.003017	0.000122	24.783	<0.001
TMP	0.5149	0.03304	15.584	<0.001
SOL_K	0.003531	0.000488	7.233	<0.001
GRAS	-0.2039	0.09001	-2.265	0.024
P_APP:PCP	-2.4E-06	5.54E-07	-4.305	<0.001
P_APP:TMP	0.000432	7.93E-05	5.445	<0.001
P_APP:GRAS	-0.03304	0.007019	-4.707	<0.001
PCP:TMP	-0.00044	2.95E-05	-14.952	<0.001
PCP:SOL_K	-1.4E-06	4.1E-07	-3.446	<0.001
PCP:GRAS	-0.00025	7.66E-05	-3.25	0.001
TMP:SOL_K	-0.00025	5.87E-05	-4.184	<0.001
TMP:GRAS	0.05117	0.009839	5.201	<0.001
P3				
Intercept	-2.817	0.2548	-11.054	<0.001
P_APP	-0.01363	0.001854	-7.352	<0.001
PCP	0.002778	0.000178	15.609	<0.001
TMP	0.1406	0.06523	2.155	0.031
SOL_K	0.00651	0.000702	9.279	<0.001

GRAN	-0.9386	0.1378	-6.812	<0.001
GRAS	-0.9931	0.1813	-5.478	<0.001
P_APP:TMP	0.003562	0.000491	7.252	<0.001
P_APP:GRAN	0.007736	0.002179	3.549	<0.001
P_APP:GRAS	-0.05489	0.01295	-4.24	<0.001
PCP:TMP	-0.0003	4.42E-05	-6.763	<0.001
PCP:SOL_K	-3.7E-06	5.78E-07	-6.359	<0.001
PCP:GRAN	0.000112	5.1E-05	2.192	0.028
PCP:GRAS	-0.00019	0.000109	-1.74	0.082
TMP:SOL_K	-0.00021	8.8E-05	-2.4	0.016
TMP:GRAN	0.1798	0.03332	5.397	<0.001
TMP:GRAS	0.247	0.03581	6.898	<0.001

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