ORIGINAL ARTICLE

Watershed and streambank erosion modeling in a coldwater stream using the GWLF-E model: application and evaluation

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Abstract

While many watershed models estimate overland flow-related soil loss, streambank erosion is often overlooked even though it can be the dominant source of sediment in a catchment. We used the enhanced generalized watershed loading functions (GWLF-E) model to simulate the water budget, field erosion from the landscape, and streambank erosion along a gradient of agricultural to urban land cover from 1997 to 2015 in the Indian Mill Creek watershed of Michigan, USA. We evaluated discharge simulations using in-streamflow measurements and evaluated streambank erosion simulations using field-collected erosion pin measurements from a previous study. Annual water budget results suggest the creek is primarily groundwater fed, but that a per-subbasin average of 6–15% of precipitation becomes runoff. Field erosion contributed a per-subbasin average of 0.5–2.5 Mg ha^{-1} year^{-1} of sediment, while streambank erosion accounted for 0.2–50.1% of the subbasins' total sediment yields. Average lateral erosion rate of streambanks in subbasins ranged from 0.04 to 7.37 cm year^{-1}, with four subbasins exceeding 1.0 cm year^{-1}. Evaluation with field-collected discharge data suggest that GWLF-E may have been overestimating discharge in the subbasins. Evaluation with streambank erosion data found that GWLF-E may have difficulty capturing the complexity of erosion rates, including instances where sediment is deposited on streambanks from upstream sources, and that it underestimates streambank erosion in headwater catchments sometimes over an order of magnitude. Our findings are important for watershed managers to evaluate modeling approaches and highlight the importance of modeling both field and streambank erosion.

Keywords Rivers/streams · Sediment · Runoff · Land use/land cover change · Watershed management

Introduction

Sediment pollution is the second-highest cause of stream degradation in the USA, impairing the health and designated uses of nearly 225,000 km of streams (USEPA, https://iaspub.epa.gov/tmdl_waters10/attains_index.home. Accessed April 25, 2020). Sediment pollution can enter a stream through various pathways including bank erosion, runoff from the landscape, and drains (Kiesel et al. 2009; Boufala et al. 2019). The movement of sediment into streams is becoming more intense because of urban and agricultural land use changes and climate change (Allan 2004; Bartolai et al. 2015). Stream sediment loads increase with agriculture and urban development in a watershed because fields,

ditches, impervious surfaces, and stormwater conveyance systems increase sediment-laden runoff and cause high peak flows that erode the banks (Allan et al. 1997; Carpenter et al. 1998; Jones et al. 2001; Paul and Meyer 2001; Allan 2004). Extreme storms and increases in runoff because of climate change can intensify erosion from landscapes and stream channels, increasing the delivery of sediment into streams (Bartolai et al. 2015). Sediment pollution negatively affects streams by reducing habitat variability, invertebrate diversity, and habitat suitability for fish (Raleigh et al. 1984; Alexander and Hansen 1986; Culp et al. 1986). It also reduces water clarity, increases water treatment costs, decreases reservoir storage area, and carries phosphorus pollution into streams (Fox et al. 2016a).

Quantifying sediment pollution on a catchment scale is important for resource management, but also problematic (Djoukbala et al. 2019; Halefom and Teshome 2019). It requires an understanding of the pathways sediment enters the water and the complex factors that affect its movement;

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data at the catchment scale may not be available (Dietrich et al. 1999; Kiesel et al. 2009). To address these problems, sediment transport to streams can be estimated using models that calculate pollutant export coefficients, loading functions, and chemical simulation (Haith and Shoemaker 1987). Data sources for the models can be readily available spatial data and/or field-collected information (Haith and Shoemaker 1987; Kiesel et al. 2009). Managers are often more focused on the distribution of erosion risk throughout a watershed than quantifying soil loss; these measured quantifications can have limitations of cost, representativeness, and reliability that make them unrealistic for assessing spatial distributions of erosion risk over a large area (Lu et al. 2004). When choosing a watershed model for a study, it is important to consider sediment pathways, incorporation of complex factors, data attainability, and the distribution of erosion risk.

The generalized watershed loading functions (GWLF) model has been used extensively in Pennsylvania, New York, Virginia, and Illinois to simulate nonpoint source pollution in watersheds and develop sediment and nutrient total maximum daily loads (TMDLs) (Evans et al. 2003; Borah et al. 2006). GWLF is a mid-range process-based model that predicts the transport of water, sediment, and nutrients in a watershed (Haith and Shoemaker 1987; Shoemaker et al. 1997, 2005). GWLF uses readily available spatial data including land cover, soil characteristics, precipitation patterns, and topography to estimate pollutant loads and hydrological regimes (Haith and Shoemaker 1987). An advantage of GWLF is that it is easy to use and relies on simpler data inputs than other more complex watershed models (Markel et al. 2006). Another advantage is that GWLF can be used in watersheds without gauges and with mixed land uses (Borah et al. 2006). The limitation of the model is the degree of uncertainty. Different sources of input data can cause changes in loading outputs that affect pollutant load requirements. For example, using land cover data from the National Land Cover Dataset versus the Digital Ortho-Quarter Quads in the GWLF model can change TMDL reduction estimates from 13 to 74% (Wagner et al. 2007). However, we deem the GWLF model appropriate for this study, because we are assessing the spatial distribution of sediment loading in the watershed rather than defining numerical targets.

A major need for research in watershed modeling is the prediction of sediment export from streambank erosion, which can be the primary contributor of alluvial materials to streams (Fox et al. 2016a). This makes streambank erosion a very important component, though often absent, in sediment TMDLs (McMillan et al. 2018). Streambank erosion is difficult to model because of complex environmental factors and drastically varying erodibility characteristics (Fox et al. 2016b). These include groundwater seeps, channel curvature, and riparian vegetation (Fox et al. 2007; Purvis

and Fox 2016; McMillan and Hu 2017). This environmental complexity magnifies uncertainty in streambank erosion assessments (Kiesel et al. 2009).

An enhancement to the GWLF model called enhanced GWLF (GWLF-E) estimates the sediment loads of eroding streambanks at watershed and subbasin levels. It uses readily available spatial data, requires no field data, and has been refined through testing of 28 Pennsylvania watersheds and subsequent adjusting (Evans et al. 2003). It can be run with the MapShed plugin of MapWindow GIS (Penn State Institutes of Energy and the Environment, University Park, Pennsylvania, USA) or the Stroud Water Research Center's Model my Watershed website (www.wikiwatershed.org/model, accessed April 25, 2020). We used the MapShed plugin with GWLF-E model for this study because it incorporates streambank erosion, uses attainable data, and can assess the erosion risk for different subbasins of our watershed. Alternative streambank erosion models that could have been used are summarized in "Discussion".

Our purpose was to: (1) identify critical areas for sediment pollution management in the Indian Mill Creek watershed of Michigan, USA, using the GWLF-E model, and (2) evaluate simulated discharge and streambank erosion rates against field measured flow and erosion pin data from a previous study. Purpose 2 is particularly important for watershed modelers because GWLF-E is calibrated for Pennsylvania watersheds and being applied in other states. We modeled runoff and sediment loading from 20 subbasins and their matching stream sections from 1997 to 2015. We aimed to determine if agricultural areas in the upper watershed contribute the most sediment from field erosion and if urban areas in the lower watershed have the highest streambank erosion rates because of increased runoff from impervious surfaces. Our findings are valuable for watershed modelers, particularly those using the GWLF-E approach or similar models, and for researchers around the USA who aim to prioritize restoration programs to reduce sediment loadings and improve stream habitats.

Methods

Study area

Indian Mill Creek in Kent County, Michigan, USA (HUC 040500060504), is on the Michigan 303(d) list of impaired water bodies, with sediment loading and deposition identified as the cause of impairment (Sigdel 2017). It is a tributary to the Grand River and is 18.5 km long with a 44 km^2 watershed (Fig. 1). The creek resides in the Southern Michigan Northern Indiana Till Plains ecoregion, characterized by irregular plains, cropland, pasture, and oak/hickory/beech/maple forests (Omernik 1987). The watershed land cover
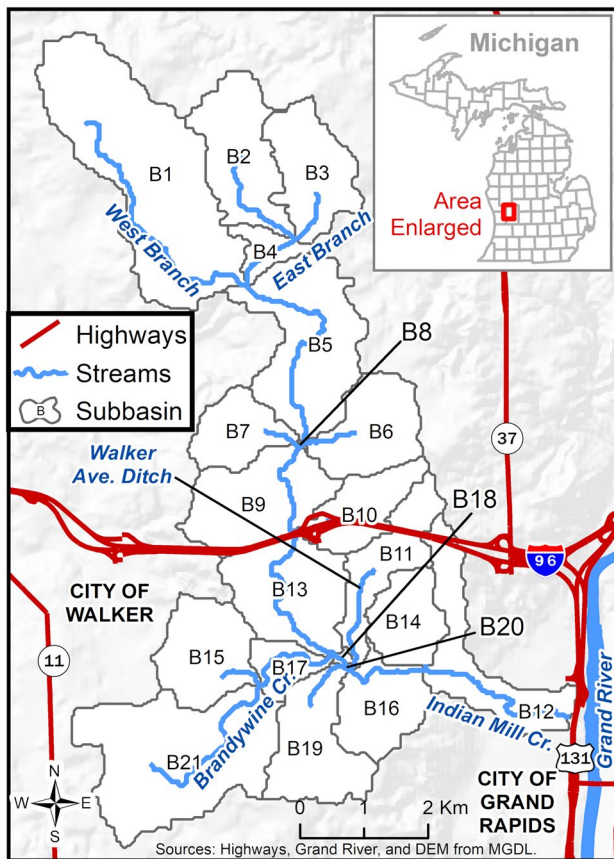
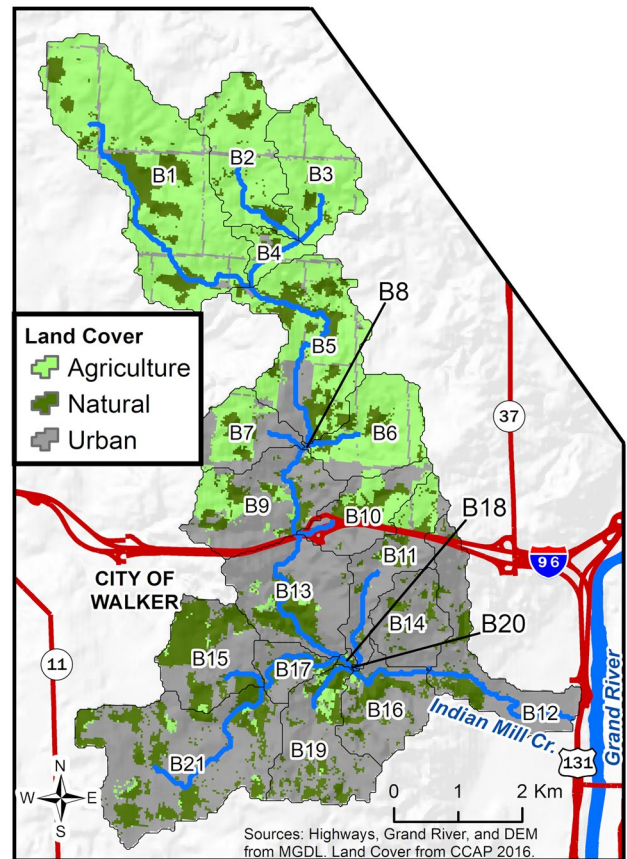**Fig. 1** Map of the Indian Mill Creek watershed

Fig. 2 Land cover of the Indian Mill Creek watershed

is predominately urban (43%) and agricultural (39%), with commercial and residential development in the lower watershed, natural and urban lands in the middle watershed, and farmland and orchards in the upper watershed (Fig. 2; Lower Grand River Watershed Plan, www.lgrow.org, accessed June 6, 2020). This land cover pattern affects the distribution of erosion risk in the watershed. The National Weather Service classifies the area as a humid continental climate with distinct summers and winters and fairly even distribution of precipitation throughout the year (www.weather.gov, Accessed April 25, 2020). Climate predictions are that the region will have more frequent extreme precipitation events, which can increase the erosion rates (Bartolai et al. 2015). Indian Mill Creek is designated as a coldwater trout stream by the State of Michigan; however, it currently does not support its coldwater fishery designated use per Michigan Department of Environmental Quality (MDEQ) standards (Water quality and pollution control in Michigan: 2016 SECTIONS 303(d), 305(b), and 314 Integrated Report, MI/DEQ/WRD-16/001).

Geologic features of the Indian Mill Creek watershed were formed by retreating glaciers that deposited hills of medium-textured till in the upper watershed (Farrand and

Bell 1982). Glacial meltwater carved the larger Grand River Valley, into which Indian Mill Creek descends for 5 km starting downstream from the present location of Interstate 96 and descending 24 m in elevation (Larson and Schaetzl 2001; Gesch et al. 2002). The side of the valley in these reaches has steep slopes, from 25 to 50% or greater along its southern edge (Fig. 3). This topography can affect erosion rates, with higher erosion in areas with steeper slopes (Wischmeier and Smith 1978). Overall, the creek descends 65 m in elevation from headwaters to mouth. The lower watershed gently slopes in an outwash of sand and gravel with postglacial alluvium (Farrand and Bell 1982). It contains alluvial hydrologic group A and B soils; however urban land areas have patchy data availability (Fig. 4) (Soil Survey Staff 2018). In contrast, the upper watershed has loamy hydrologic group C and C/D soils with low infiltration in uplands, but sandy A/D and B/D soils along the West Branch and Indian Mill Creek. The middle watershed is a transition zone and has loamy C and C/D soils in uplands and sandy A and B soils with high infiltration by the main channel and the Walker Avenue Ditch. These soils affect the distribution of runoff and erosion risk in the watershed; high runoff is associated with groups C and D soils, such as those in the upper
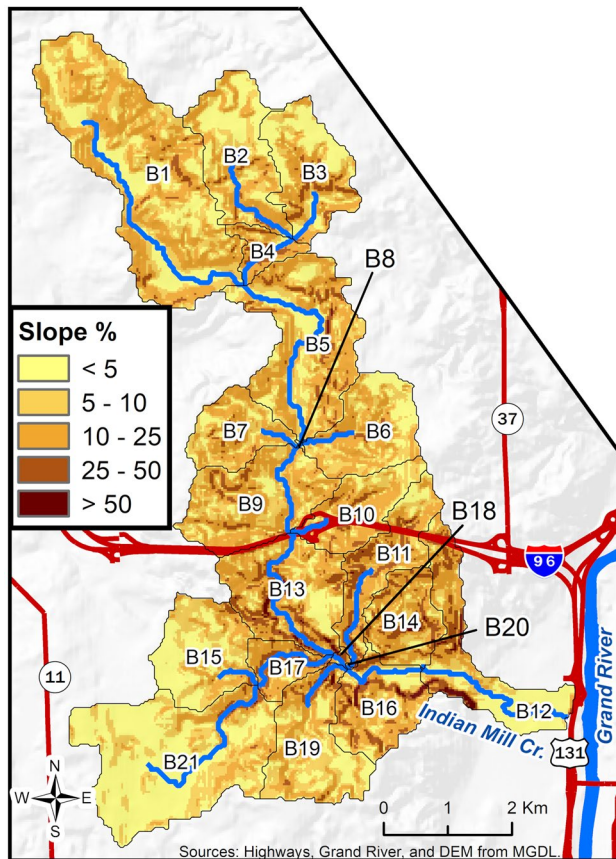
Fig. 3 Slopes of the Indian Mill Creek watershed

Fig. 4 Soil types of the Indian Mill Creek watershed

and middle watershed's uplands (U.S. Department of Agriculture, Chapter 7 of Part 630 Hydrology of the National Engineering Handbook). These soils also are associated with higher erodibility in the watershed (Soil Survey Staff 2018).

Modeling

We performed our study using Penn State's MapShed and GWLF-E models (https://wikiwatershed.org/help/model-help/mapshed/, accessed June 5, 2020) with widely available spatial data. The MapShed model uses MapWindow Geographic Information System software to create an input file for the GWLF-E model. We then used GWLF-E to process the input file and simulate watershed hydrology and pollutant loadings from 1997 to 2015. In the model, surface runoff was simulated using the runoff curve number equation (NRCS 1986; Haith and Shoemaker 1987), which is effective for calculating runoff in a watershed (Satheeshkumar et al. 2017; Velásquez-Valle et al. 2017). Field erosion was simulated using the Universal Soil Loss Equation (USLE; Wischmeier and Smith 1978), which is a reliable soil erosion model used in previous studies (Amin and Romshoo 2018;
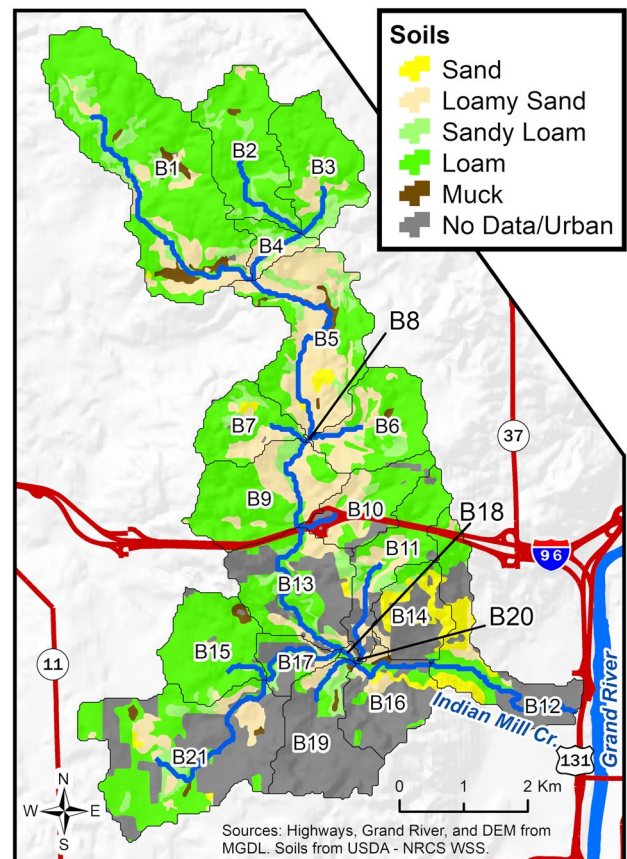
Djoukbala et al. 2019). GWLF-E simulated streambank erosion using the lateral erosion rate (LER) equation

$$LER = aQ^{0.6}$$

where LER is units of meters per month, a is an erosion potential factor derived from empirical data, and Q is the mean monthly streamflow in $m^3 s^{-1}$ (Evans et al. 2003). The LER in GWLF-E is then multiplied by a default bulk density $(1.5 Mg (m^3)^{-1})$, default bank height (1.5 m), and length of stream in the subbasin (m) to calculate sediment load from bank erosion (Evans et al. 2003).

We collected spatial data for the MapShed model from multiple sources. We delineated 20 subbasins and streams using the Watershed Delineation plugin of MapWindow and elevation data from a 30 m digital elevation model from the National Elevation Dataset (Gesch et al. 2002). We used land cover data from the National Oceanographic and Atmospheric Administration Coastal Change Analysis Program (Office for Coastal Management 2016). We downloaded Spatial Soil Survey Geographic Database (SSURGO) soils data from the Natural Resources Conservation Service's Web Soil Survey and joined it with tabular data (Soil

Survey Staff 2018). Soils of the urban land type and gaps in soil data availability in the lower watershed interfered with the model; we thus assumed them to be impervious surfaces assigned a soil erodibility factor of zero, hydrologic group D, and available water capacity of zero. These soils were in an urban area covered extensively with parking lots, buildings, and roads and the above-mentioned criteria were assigned to simulate the imperviousness. We downloaded precipitation and temperature data from Michigan Enviro-Weather's Sparta station (https://www.enviroweather.msu.edu, Accessed April 25, 2020) that had the desired time span of data. We calculated streamflow volume adjustment factors automatically in MapShed to account for the contribution of streamflow from the upper basins to lower basins (MapShed Version 1.5 Users Guide, https://wikiwatershed.org/help/model-help/mapshed/, accessed June 6, 2020).

We created a GWLF-E input file for each subbasin for the years of available weather data (1997–2015) and a growing season of May–September. Lateral erosion rate (LER) was calculated from the outputs by dividing the mass of erosion by the GWLF-E's default bulk density (1.5 Mg $(m^3)^{-1}$), default bank height (1.5 m), and length of stream in the subbasin (m).

Discharge estimate evaluation

We evaluated the reliability of GWLF-E discharge estimates by comparing outputs with manually collected discharge data. We measured stream discharge in transects during seven monitoring events in 2017 at 60% depth with a Marsh-McBirney Flow Mate 2000 velocity meter (Hach Company, Loveland, CO) attached to a top-setting wading rod. These events were May 30, June 15, June 20, July 13, July 25, August 24, and September 12. June 15 and July 13 were rain events, while the other samples were of baseflow. We then simulated the GWLF-E model for 2017; average daily discharges for those sampling events were extracted from the results and converted to $m^3 \ s^{-1}$. We averaged this estimate for each site and compared it with the average discharge collected by the flow meter.

Streambank erosion evaluation

We evaluated the streambank erosion routine of the GWLF-E model in the Indian Mill Creek watershed using field-collected streambank erosion data from a 2017–2018 study (Myers et al. 2019). This study measured streambank erosion rates over the course of 1 year (May 12, 2017–May 4, 2018) at nine study sites, including the mainstem of Indian Mill Creek and the Brandywine Creek and Walker Ditch tributaries. At each study site, erosion pins were placed over an 18 m section of streambank on both sides of the creek. Lateral erosion rate was estimated by taking the mean erosion

rate of the pins along each bank and then calculating a grand mean of the streambanks for the site. In total, 137 pins were measured. These results were compared with the average annual LER from the GWLF-E subbasins, simulated for the period May 2017 through April 2018.

Results

Water budget

We simulated the water budget, field erosion, and streambank erosion outputs from the GWLF-E model for 20 subbasins (Table 1). Annual water budget results suggest that Indian Mill Creek is primarily a groundwater fed stream. Approximately, 85 cm of precipitation falls in the watershed annually. Evapotranspiration removes between 16 and 23% of this water depending on the subbasin. The remaining water feeds the creek as either groundwater flow or runoff. Groundwater flow contributes a per-subbasin average of 63–78% of the stream flow. The other 6–15% of the precipitation in subbasins becomes overland runoff and is quickly exported from the subbasins. Urbanized subbasins in the southern part of the watershed have the highest proportion of water becoming runoff, especially in subbasins of Brandywine Creek (Fig. 5).

Sediment loading

The sediment loading outputs of the GWLF-E model predict that the creek receives a total load of 6109 Mg $year^{-1}$ of sediment from field and streambank erosion. Field erosion contributes an average by subbasin of 0.2–2.5 Mg ha^{-1} $year^{-1}$ of sediment to the creek. The greatest rates of field erosion occur in the middle and southern subbasins of the watershed (Fig. 6). Streambank erosion contributes an average by subbasin of 0.2–508.6 Mg $year^{-1}$ of sediment to the creek, accounting for 0.2–50.1% of the subbasins' sediment budgets (Fig. 7). The lateral erosion rate of streambanks varied by subbasin from 0.04 to 7.37 cm $year^{-1}$. Both the proportion of sediment load from streambanks and the lateral erosion rate increased in a downstream direction, with less erosion in the headwaters and more erosion in lower reaches (Figs. 7, 8). Total sediment loading varied by subbasin, but was greatest in the lowest segment BC12 (Fig. 9).

Discharge evaluation

Our evaluation of GWLF-E discharge estimates shows that they follow the same pattern as manually collected estimates of increasing discharge closer to the outlet of

Table 1 Results from the GWLF-E model for 21 subbasins in the Indian Mill Creek Watershed 1997–2015. Subbasins B1–B8 are in the upper watershed, dominated by agricultural land cover, and B9–21 are in the middle to lower watershed, dominated by urban land cover, with spatial reference in Fig. 1

Geography		Annual water budget				Annual field erosion		Annual streambank erosion		
Basin	Area (ha)	Precipitation (cm year^{-1})	Evapotranspiration (%)	Groundwater (%)	Runoff (%)	Mg	Mg ha^{-1}	Mg	% of sediment load (%)	LER
B1	677	85	21	69	11	924.4	1.4	9.5	1.0	0.09
B2	247	85	22	68	10	266.0	1.1	2.7	1.0	0.06
B3	212	85	21	69	10	199.8	0.9	0.9	0.5	0.04
B4	57	85	20	71	9	38.8	0.7	5.9	13.2	0.22
B5	374	85	20	74	6	579.5	1.5	21.3	3.6	0.24
B6	200	85	21	68	11	279.8	1.4	0.8	0.3	0.04
B7	136	85	22	68	10	176.3	1.3	0.7	0.4	0.04
B8	1	85	16	78	6	1.8	1.2	1.8	50.1	0.61
B9	272	85	22	67	11	539.8	2.0	43.6	7.5	1.15
B10	151	85	21	66	12	125.8	0.8	3.3	2.6	0.20
B11	178	85	22	67	11	275.0	1.5	6.4	2.3	0.15
B12	238	85	21	66	13	593.2	2.5	508.6	46.2	7.37
B13	269	85	21	65	14	505.9	1.9	271.4	34.9	3.98
B14	145	85	21	69	11	109.5	0.8	0.2	0.2	0.11
B15	209	85	23	63	14	128.9	0.6	1.5	1.1	0.08
B16	180	85	21	67	13	151.0	0.8	116.5	43.5	3.49
B17	74	85	21	67	12	47.7	0.6	10.1	17.5	0.25
B18	6	85	16	74	10	11.5	1.9	11.0	48.9	1.53
B19	232	85	20	67	14	39.5	0.2	1.6	4.0	0.07
B21	518	85	21	63	15	83.7	0.2	13.5	13.9	0.19

LER lateral erosion rate in cm year^{-1}

Indian Mill Creek (Fig. 10). However, GWLF-E can overestimate discharge by a factor of up to 11.0 compared with collected discharge estimates in headwater subbasins like B21, and by a factor of 2.8 by the outlet of the creek (B12). Subbasin B11 had patchy data because of its creek's ephemeral nature.

Streambank erosion evaluation

Our evaluation of GWLF-E streambank erosion estimates found that streambank erosion rates may be more complex than were simulated. For example, the erosion pin measurements did not agree with the increasing erosion downstream pattern of GWLF-E (Fig. 11). Some banks experienced more deposition of sediment over the course of the year from erosional areas upstream. This was observed at subbasins B9 and B12 in the lower watershed. Also, the evaluation suggests that GWLF-E may be underestimating erosion rates in headwater streams by more than an order of magnitude, as the simulated LER for headwater subbasin B1 was of 0.10 cm year^{-1} while erosion pin data suggest the LER was 4.5 cm year^{-1}.

Discussion

The transport of water and sediment through watersheds is affected by a combination of soils, topography, land cover, and climate. Knowledge of these relationships is important for nonpoint source pollution management and predicting impacts from climate change. Relationships can be interrelated and complex; a watershed model can piece together their story and identify critical areas for nonpoint source pollution management. We created a map with recommendations for each subbasin based on land cover data and proximity to the creek (Fig. 12) and identified subbasins as critical areas for runoff, field erosion, and/or streambank erosion management.

Runoff

Watershed models provide an opportunity for managers to understand runoff patterns and plan mitigation projects accordingly (Chadli et al. 2016). The Brandywine Creek area in the southwest portion of the watershed proportionally contributed the greatest amount of runoff to the creek and the least amount of groundwater to feed base flow. A
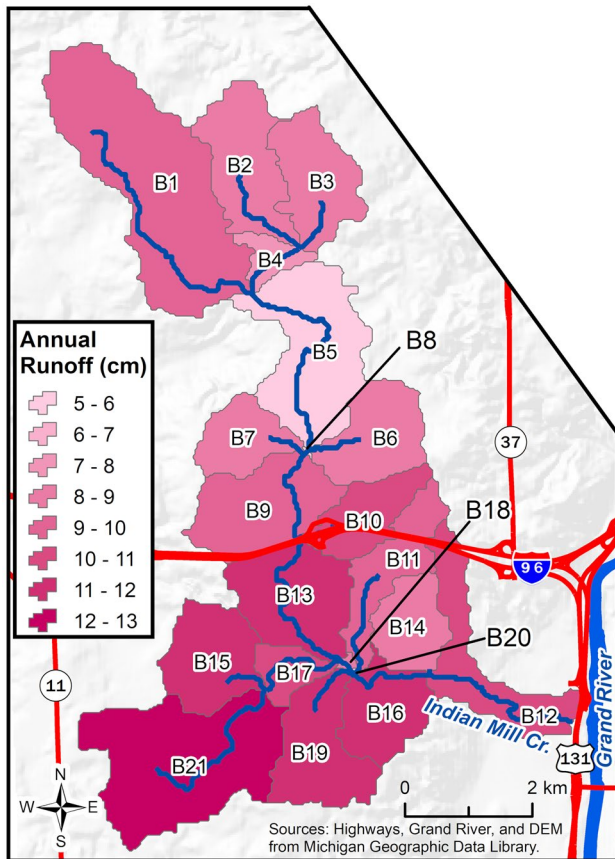
Fig. 5 Annual runoff results from the GWLF-E model for subbasins in the Indian Mill Creek watershed 1997–2015
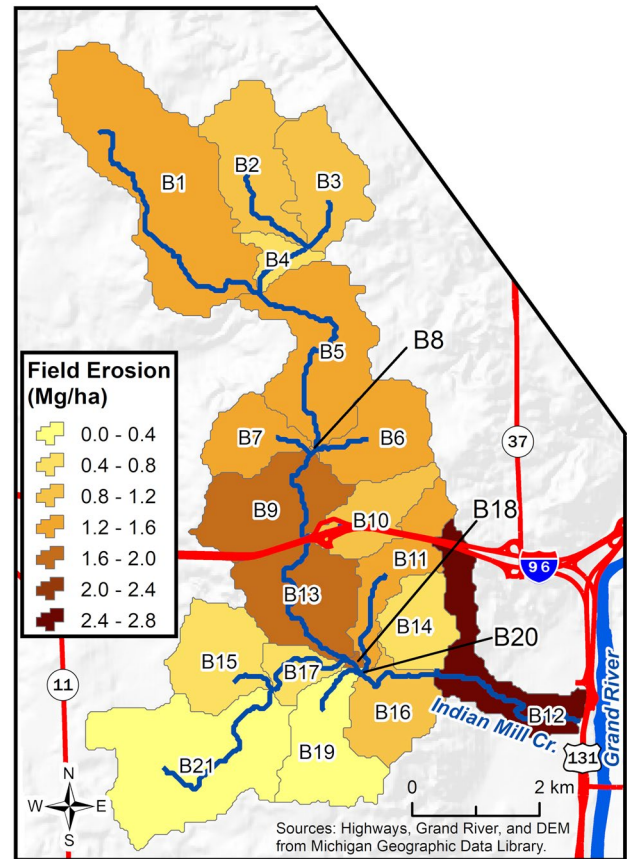

Fig. 6 Annual field erosion results from the GWLF-E model for subbasins in the Indian Mill Creek watershed 1997–2015

very low base flow in mid-summer and evidence of powerful floods after rain storms were observed in the adjacent grassy floodplain (Fig. 13). This flow regime is likely caused by loamy soils of the C and D hydrologic groups with high runoff potential plus the high amount of urban development and impervious surfaces in the subbasin, which cause increased runoff and decreased infiltration of water to the soil (Paul and Meyer 2001). Subbasin B21, the headwaters of Brandywine Creek, should be a priority for mitigation projects that capture runoff and increase infiltration. This reduction in runoff is vital to restoration of the watershed, as restoring stream habitat and riparian conditions in urban streams can be ineffective for recovery of aquatic life if the impacts of intense stormflows are not addressed (Walsh et al. 2005).

Field erosion

The GWLF-E model predicted that subbasins with high sediment loading from field erosion were spread throughout the watershed. Urbanized subbasins along the middle and southern areas of the watershed had the highest predicted per hectare rates of field erosion. This was different from what we expected and could be explained by a combination of steep slopes, erodible soils, and urban land cover that increased the risk of field erosion (Wischmeier and Smith 1978; Paul and Meyer 2001; Lu et al. 2004). However, agricultural subbasins in the upper watershed still contributed considerable sediment to the creek by field erosion and were no less important for nonpoint source pollution management. We identified critical areas for agricultural best management and low impact development practices to manage field erosion based on their per hectare contribution of sediment to the creek. Subbasin B12 should be a priority for field erosion management, followed by B9, B18, B13, and B5. Field erosion results were consistent with Wagner et al. (Wagner et al. 2007), which modeled rates of 0.4–2.8 Mg ha^{-1} year^{-1} in four Virginia catchments with the GWLF model. Our results also were similar to Kiesel et al. (Kiesel et al. 2009), which modeled rates of 0–3.5 Mg ha^{-1} year^{-1} in a lowland German catchment using a German revision of the Universal Soil Loss Equation.
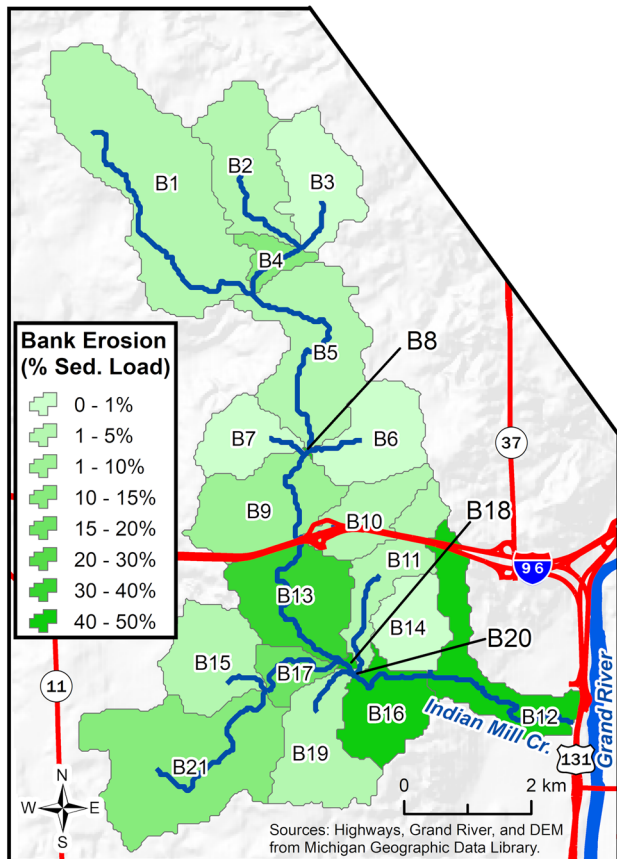
Fig. 7 Percent of total sediment load from bank erosion from the GWLF-E model for subbasins in the Indian Mill Creek watershed 1997–2015
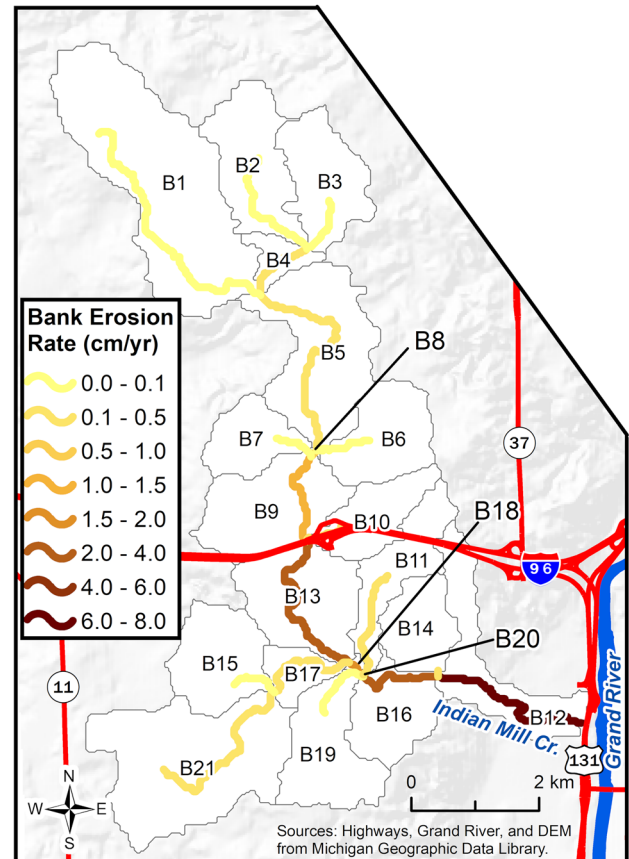

Fig. 8 Lateral streambank erosion rates from the GWLF-E model for subbasins in the Indian Mill Creek watershed 1997–2015

Streambank erosion

The rate of sediment loading from streambank erosion modeled with GWLF-E followed a longitudinal pattern in the watershed. GWLF-E predicted streambanks in headwater subbasins would experience low lateral erosion rates and yield a small fraction of the overall sediment load. The simulations also showed that the lateral erosion rate increased in a downstream direction along with the proportion of sediment loading from streambank erosion, predicting that urban areas in the lower watershed would have the highest erosion rates. This longitudinal pattern was an effect of the GWLF-E streambank erosion model, which relied on the effect of mean monthly discharge to calculate erosion rates (Evans et al. 2003). Field-collected flow data by the authors from five dry and two storm sampling events in May–September 2017 confirmed that there was a trend of increasing discharge from headwaters to mouth of the creek that could affect erosion rates (Fig. 10). Thus, the stream corridor of the lower watershed should be a critical area for streambank erosion control. This corridor had the largest

modeled streambank erosion rates because the subbasins had the strongest discharge. Erodible sandy soils in the streambanks observed in the lower watershed could also influence the high erosion rates (Fig. 14). Bank erosion results were consistent with Kiesel et al. (2009), who measured rates of 0.1–12.8 cm year^{-1} in a lowland German catchment; Zaimes et al. (2005), who measured mean bank erosion rates of 0.7–5.1 cm year^{-1} in Iowa, USA streambanks; and Laubel et al. (1999), who measured mean rates of 0.6–2.6 cm year^{-1} in a Danish watershed.

The GWLF-E did not identify subbasin B11, the Walker Avenue Ditch, as a priority for streambank erosion. However, we have observed severe erosion occurring in B11 along with intensive sedimentation in the streambed, which appears to be among the worst in the Indian Mill Creek watershed (Fig. 15). Further, the evaluation of nine study sites from the previous study (Myers et al. 2019) suggested that actual streambank erosion rates in the watershed may be more complex than simulated by GWLF-E and that streambank erosion was underestimated in headwater subbasins. This could make these headwater subbasins a higher priority for streambank erosion control than was simulated with the

Fig. 9 Total annual subbasin sediment loading from field and bank erosion from the GWLF-E model in the Indian Mill Creek watershed 1997–2015
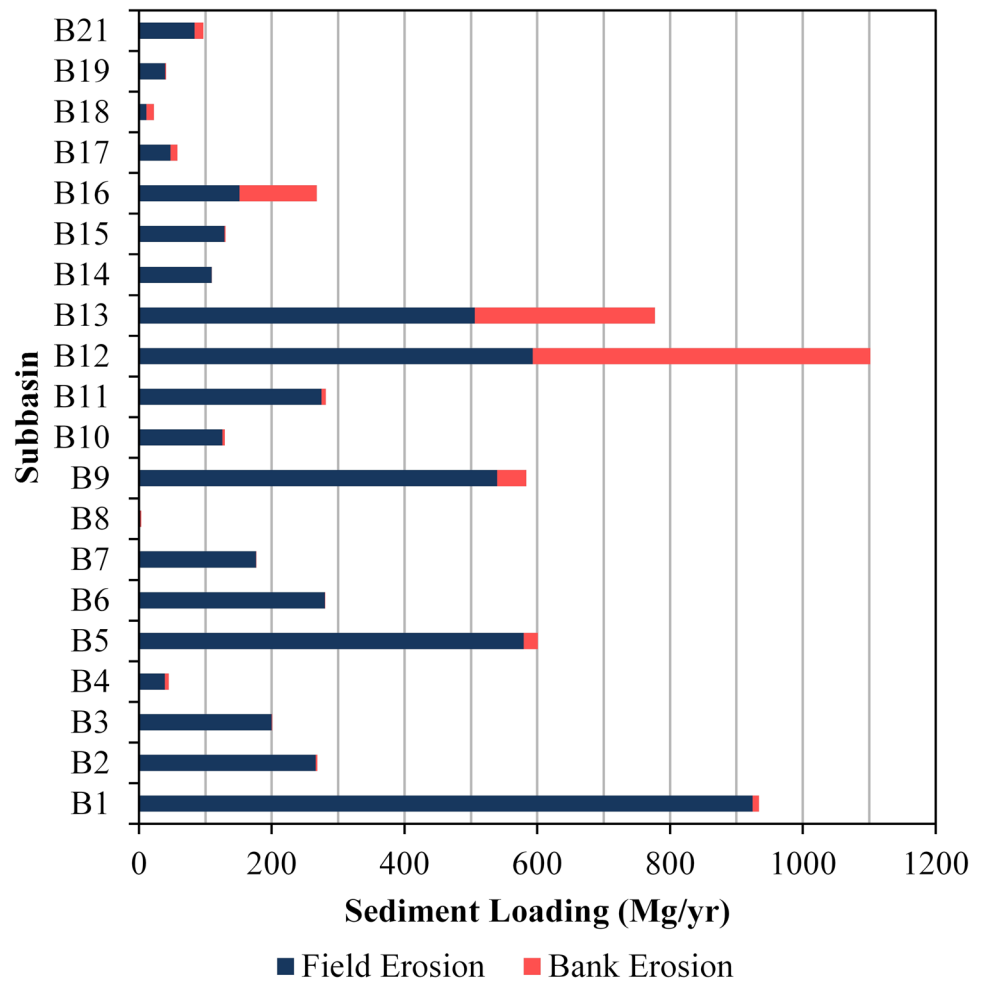

Fig. 10 GWLF-E discharge evaluation using manually collected discharge data, averaged in eight subbasins over seven monitoring events in 2017. B2, B11, and B21 are tributaries while B1 to B12 progress from headwaters to the outlet of Indian Mill Creek
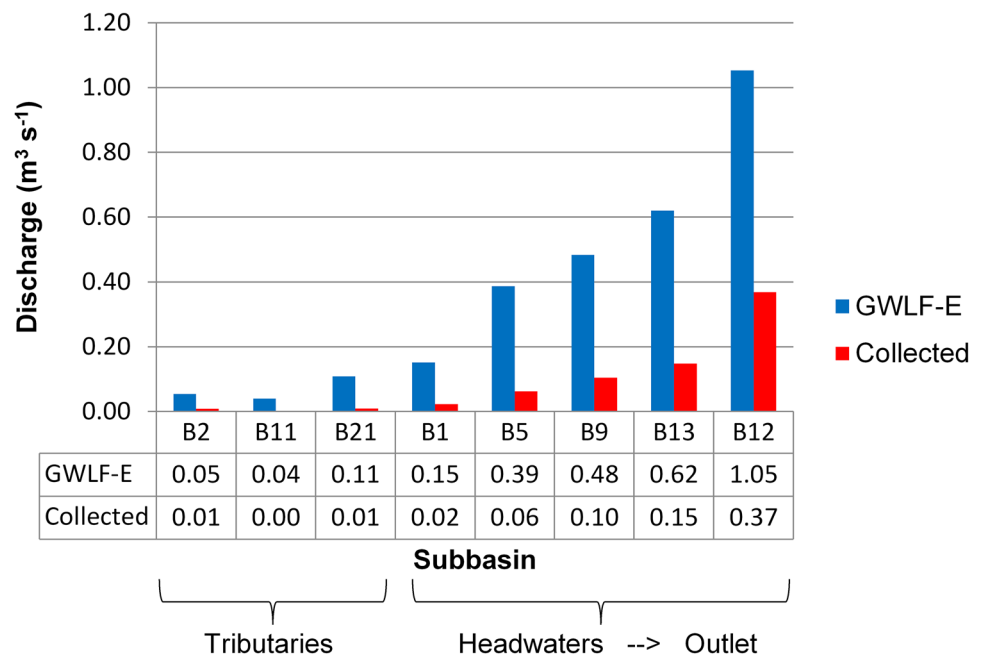

	B2	B11	B21	B1	B5	B9	B13	B12
GWLF-E	0.05	0.04	0.11	0.15	0.39	0.48	0.62	1.05
Collected	0.01	0.00	0.01	0.02	0.06	0.10	0.15	0.37

Fig. 11 GWLF-E annual lateral erosion rate evaluation using erosion pin data from Myers et al. (2019) from May 2017 through April 2018. Bars are labeled with the site names of the erosion pin measurements from that study
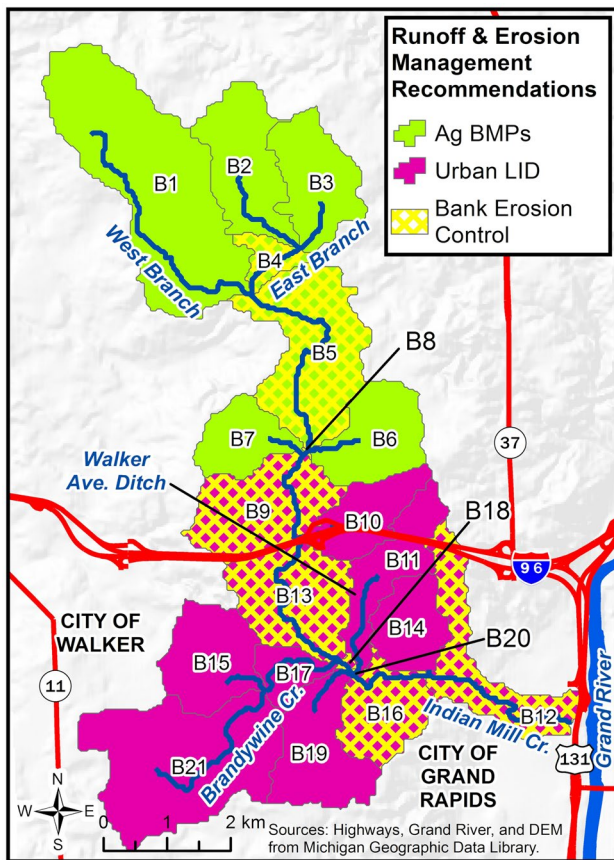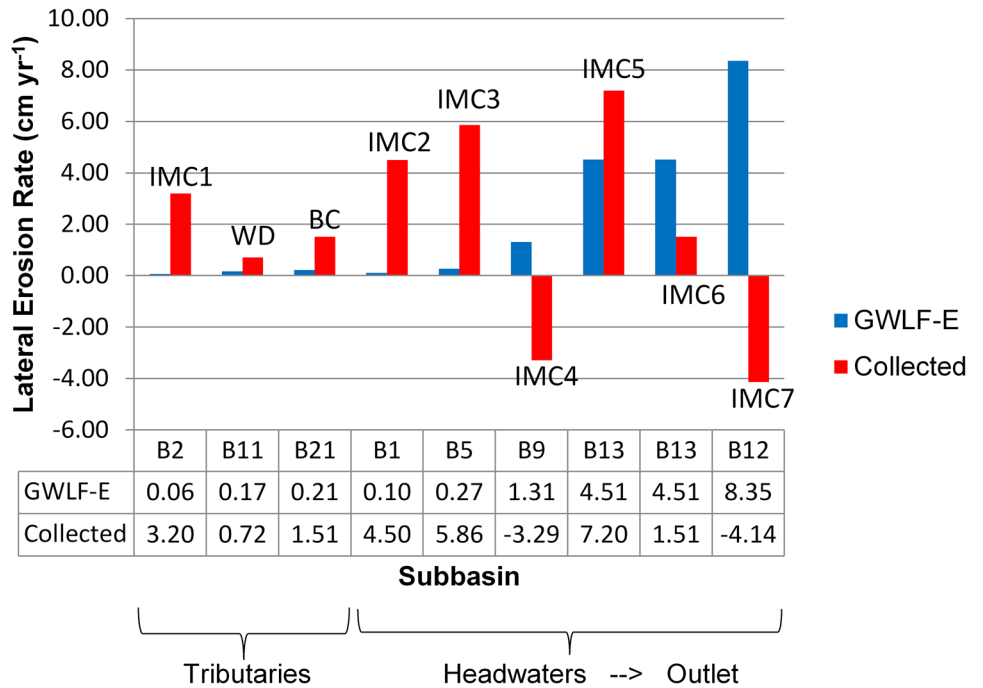

Subbasin	B2	B11	B21	B1	B5	B9	B13	B13	B12
GWLF-E	0.06	0.17	0.21	0.10	0.27	1.31	4.51	4.51	8.35
Collected	3.20	0.72	1.51	4.50	5.86	-3.29	7.20	1.51	-4.14

Fig. 12 Runoff and erosion management recommendations including agricultural best management practices (Ag BMPs), urban low impact development (LID), and streambank erosion control for subbasins in the Indian Mill Creek watershed
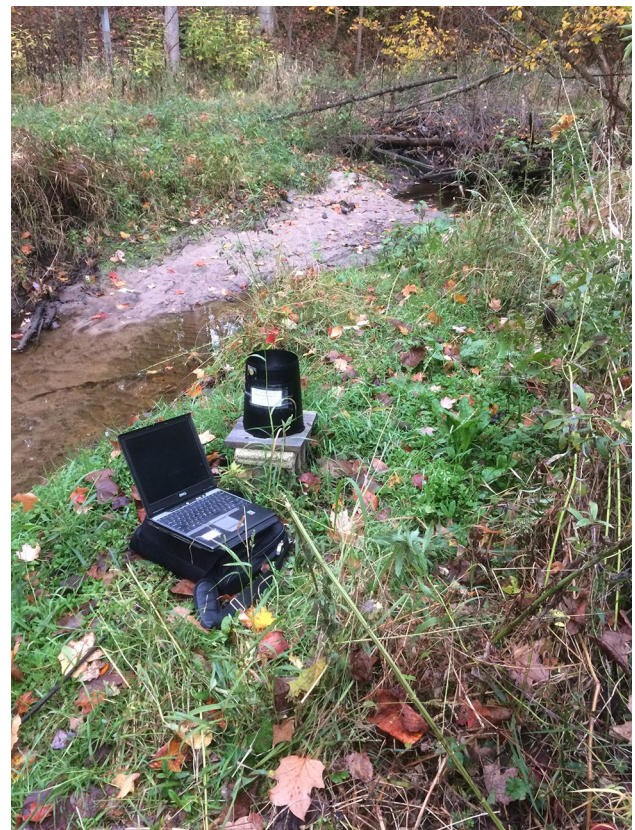

Fig. 13 Flood-washed grass along Brandywine Creek in the Indian Mill Creek watershed, October 2017

Fig. 14 Sandy eroding banks observed in subbasin B12 in the lower Indian Mill Creek watershed, April 2017

Fig. 15 Severe incising and bank erosion observed in Walker Avenue Ditch (subbasin B11) of the Indian Mill Creek watershed, April 2017

model. These distinctions are important to be aware of for researchers using the GWLF-E model for catchments outside of the Pennsylvania watersheds it was calibrated with and for watershed modelers evaluating streambank erosion models.

Alternative models

Various models can be used to estimate streambank erosion rates in a watershed. However, they often require extensive field data collection. Here, we summarize four additional streambank erosion models that could have been used for this study and their limitations. We chose the GWLF-E model because it fits our purpose of assessing erosion risk in subbasins throughout the watershed, has attainable data, and does not require extensive field data collection.

The Bank Stability and Toe Erosion Model (BSTEM) from the National Sedimentation Laboratory will predict streambank erosion and loading rates based on hydrology and field measurements (Simon et al. 2011; Midgley et al. 2012). BSTEM is built in a spreadsheet and can evaluate bank stability over changing hydrological conditions (Simon et al. 2011). The model uses field data about channel geometry and soil properties, including jet soil tests (Midgley et al. 2012), which could make it more intensive to implement on a watershed scale.

The Bank Assessment of Nonpoint Source Consequences of Sediment (BANCS) model is widely used for stream restoration and estimating sediment yields (Sass and Keane 2012; McMillan et al. 2018). It uses the qualitative visual Bank Erosion Hazard Index (Rosgen 2001) to estimate bank erosion rates. It however relies on visual estimates and an evaluation of the model deemed it uncorrelated with actual erosion rates (McMillan et al. 2018).

The Soil and Water Assessment Tool (SWAT) uses the critical sheer stress equation to estimate the sediment loading of bank erosion in a watershed (Mittelstet et al. 2017; Narasimhan et al. 2017). Similar to the GWLF model, SWAT uses spatial data about land cover, soils, weather, and slopes. It also can incorporate data about channel morphology collected in the field (Mittelstet et al. 2017). The SWAT model has been shown to reasonably account for complex streambank factors and estimate erosion rates that are similar to field measurements (Narasimhan et al. 2017). However, the SWAT model can involve extensive calibration with field data and more complex datasets than the GWLF model (Shoemaker et al. 2005; Markel et al. 2006).

The Dickinson–Scott model is a regression equation that is used to estimate streambank erosion rates (Dickinson and Scott 1979). This model uses soil erodibility, an agricultural intensity index, and a hydraulic stability index to estimate lateral erosion rates (Dickinson et al. 1989). The Dickinson–Scott model was developed to assess streambank erosion in agricultural catchments of southern Ontario and modified for lowland catchments in Germany (Dickinson and Scott 1979; Kiesel et al. 2009). Limitations are that it does not account for flow regime, bank slope, and bank vegetation (Kiesel et al. 2009).

Study limitations

The GWLF-E model tended to overestimate discharges throughout the watershed. This overestimate could be explained by the model not being calibrated to Indian Mill Creek or that it is predicting greater storage of water, leading to higher base flow estimates. Implications of this are that the model is appropriate for assessing spatial distribution of erosion risk, but could be less effective for numerical targets without calibration. The model could be overestimating stream discharge in our study stream because it was validated for Pennsylvania watersheds (Evans et al. 2003) and not our study stream. Also, the GWLF-E streambank erosion model assumes a uniform discharge, lateral erosion rate, bank height, and soil bulk density for the entire length of stream in a basin (Evans et al. 2003). The bank height and soil bulk density are default values of 1.5 m and 1500 kg $(m^3)^{-1}$ and can vary in nature, resulting in some stream segments not fitting model predictions. We observed that incised segments of lower Indian Mill Creek can have taller banks of two or more meters, while small tributaries can have much shorter bank heights of less than a meter. Additionally, GWLF-E assumes that streambank erosion occurs at all discharges. Other studies suggest that streambank erosion occurs only after the force of discharge passes a certain threshold called the soil's critical sheer stress (Mittelstet et al. 2017; Narasimhan et al. 2017). These complexities could help explain why the GWLF-E LER simulations and erosion pin measurements would disagree in some subbasins.

Conclusion

A major cause of stream degradation in the USA is sediment pollution. Data can be unrealistic to collect at the catchment scale, so decision makers often turn to models that simulate sediment transport to better manage sediment in their catchments. The simulation of streambank erosion is an area in need of more research because it can be the dominant source of sediment to streams in a catchment. GWLF-E can help managers identify critical areas for restoration and prioritize projects to reduce nonpoint source pollution. The ease of use of MapShed and the GWLF-E model make them relevant to other watershed studies as long as model limitations are considered. Evaluations of these limitations suggests that GWLF-E may overestimate discharge in the catchment and have difficulty simulating complex streambank erosion rates. Future research needs include investigations of critical catchments to further understand their contribution of water and sediment to Indian Mill Creek, use of the GLWF-E model to track implementation of best management practices into the future, and comparison studies between the streambank erosion routines of GWLF-E and other models. Further research

to improve the streambank erosion simulation ability of the GWLF-E model is recommended.

Electronic data

MapShed input data, GWLF-E input files, and GWLF-E output files are in published Myers et al. Supplementary Material.zip through Mendeley Data (https://dx.doi.org/10.17632/xjxk9x9wjc.2). These files can be used with MapShed and GWLF-E to replicate the study.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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