Impact of Spatial Discretization of Hydrologic Models on Spatial Distribution of Nonpoint Source Pollution Hotspots

Yan Wang[1]; Hubert J. Montas[2]; Kaye L. Brubaker[3]; Paul T. Leisnham[4]; Adel Shirmohammadi[5]; Victoria Chanse[6]; and Amanda K. Rockler[7]

Abstract: The soil and water assessment tool (SWAT) was used to investigate the effects of hydrologic response unit (HRU) thresholds (0–20%) on predictions of multiple variables by calibrated and uncalibrated models in a 10.4-km^2 urban watershed in the U.S. Mid-Atlantic region. Surface runoff, discharge, sediment yield, and nutrient yield were simulated in stream and on land, and used to spatially identify hotspots for each constituent. *SWAT2012* was able to produce accurate discharge and nitrogen estimates that were not sensitive to HRU thresholds. HRU thresholds significantly affected sediment and phosphorus predictions in calibrated and uncalibrated models. Constituent hotspots identified by an uncalibrated model with a 0% HRU threshold were found to be acceptable for the urban watershed under study, except for sediment. Hotspots identified with calibrated models, with HRU thresholds of 5% or less, fit with the identification of on-land sediment and nutrient hotspots. These findings suggest that researchers should carefully consider HRU thresholds when predicting on-land variables of small urban watersheds similar to the watershed in this study when using SWAT. **DOI: 10.1061/(ASCE)HE.1943-5584.0001455.**

Author keywords: Spatial distribution; Nonpoint pollution; Stormwater management; Hydrologic models; Geographic information systems.

Introduction

Hydrologic and environmental models play an important role in providing reliable and accurate information that serves as a base for environmental assessment and decision making (Djodjic et al. 2002; Zadeh et al. 2007; Panagopoulos et al. 2012). The accuracy of a model simulation and the associated uncertainty are directly related to environmental management action and related decision making.

Hydrologic models simulate water cycles and the associated sediment, nutrients, and microbes, and thus are used to quantify the impact of human activities on water processes (Singh and Frevert 2010). Distributed hydrologic models, which are capable of targeting sensitive spots in a watershed, are increasingly used. The nature of spatially distributed models requires that their inputs also be spatially distributed at some scale of resolution. Rapid development of geographic information systems (GIS) has allowed hydrologic models to include more information regarding watershed characteristics, thus enabling relatively reasonable simulations. However, assuming that all input data are close to reality, the models themselves can be quite sensitive to different resolutions of both spatial and temporal data (Abbott and Refsgaard 1996). Current analyses of model sensitivity to GIS input data focus on two aspects: spatial resolution of input parameters and delineation of subbasins. In other words, grid cell size and number of subbasins are considered important factors in watershed assessment by current hydrologic and water quality models.

Hydrologic models are quite sensitive to the resolution of input data such as digital elevation models (DEMs), soil maps, land use maps, and other spatially distributed physical and biological watershed characteristics. Resolution significantly affects the delineation of stream networks and subbasins and the simulation of sediment, nonpoint source (NPS) pollution, peak runoff, and other local hydrological processes (Brown et al. 1993; Vieux and Needham 1993; Zhang and Montgomery 1994; Blöschl and Sivapalan 1995; Kuo et al. 1999; Kalin et al. 2003; Chaplot 2005; Romanowicz 2005; Chaubey et al. 2005; Hessel 2005; Dutta and Nakayama 2009). The number of subbasins in a hydrologic model also plays an important role in model performance, especially in simulations of sediment and nutrients (Mamillapalli et al. 1996; FitzHugh and MacKay 2000; Jha et al. 2004). A review of the literature indicates that two issues lack consideration. First, almost all research has focused either on the cell sizes of input files, with cells essentially the smallest mapping unit in GIS, or on subbasin size. It has largely overlooked the importance of the size and number of basic calculation units of a hydrologic model. Second, in-stream variables such as stream discharge, total sediment, and nutrient yield at the outlet of the watershed/subbasins have been analyzed without connecting them to the upland sources in a more spatially distributed manner for targeting purposes.

The first issue is worth consideration where the smallest mapping unit is different from the smallest calculation unit in

[1]Graduate Student, Dept. of Civil and Environmental Engineering, Univ. of Maryland, College Park, MD 20742 (corresponding author). E-mail: wangyan@umd.edu

[2]Professor, Dept. of Bio-Engineering, Univ. of Maryland, College Park, MD 20742. E-mail: montas@umd.edu

[3]Associate Professor, Dept. of Civil and Environmental Engineering, Univ. of Maryland, College Park, MD 20742. E-mail: kbru@umd.edu

[4]Associate Professor, Dept. of Environmental Science and Technology, Univ. of Maryland, College Park, MD 20742. E-mail: leisnham@umd.edu

[5]Professor, Dept. of Environmental Science and Technology, Univ. of Maryland, College Park, MD 20742. E-mail: ashirmo@umd.edu

[6]Assistant Professor, Dept. of Plant Science and Landscape Architecture, Univ. of Maryland, College Park, MD 20742. E-mail: vchanse@umd.edu

[7]Agent, Maryland Sea Grant Extension Programs, Univ. of Maryland, College Park, MD 20742. E-mail: arockler@umd.edu

Note. This manuscript was submitted on January 11, 2015; approved on July 12, 2016; published online on August 16, 2016. Discussion period open until January 16, 2017; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Hydrologic Engineering***, © ASCE, ISSN 1084-0699.

semidistributed hydrologic models such as the soil and water assessment tool (SWAT) (Neitsch et al. 2011). SWAT was developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch et al. 2011).

The basic calculation unit of SWAT is the hydrologic response unit (HRU), which represents a unique combination (UC) of land use, soil type, and slope class. The size of each UC cannot be smaller than the DEM cell size. Therefore, the number and the minimum area of HRUs in a SWAT model and DEM cell size are closely relateds. Because not all UCs are necessarily defined as HRUs, two SWAT models may have different numbers of HRUs when using the same DEM and land use, and soil maps. When preparing SWAT input files, the number of HRUs can be defined in a process called HRU definition, in which a user defines certain thresholds, either as a percentage of the subbasin area or as a specific area, for land use, soil type, and slope class, and define which UC should be modeled as an HRU. A threshold of 10% land use means that if the area of a certain land use in the subbasin is less than 10% of the total area of this particular subbasin, no UC associated with this land use is defined as an HRU. The SWAT simulation time is partly related to the number of HRUs defined in a model. HRU definition has therefore been used for reducing simulation time but maintaining most of the watershed characteristics. Any UC in the subbasin that is not defined as an HRU is integrated with all other defined HRUs according to the HRUs' area ratio. A general rule of applying 10% land use, 10% soil type, and 0% slope threshold values for HRU definition has been widely accepted (Winchell et al. 2007). However, little research has been done to validate this approach. Moreover, little sensitivity analysis has been conducted on model performance when the model only varies the number of defined HRUs.

In-stream variables are no longer the only concern in water quality studies. On-land variables are gaining more attention from hydrologists, with research growing in stormwater management and NPS pollution. Nonpoint source pollution hotspots are also referred to as critical source areas (CSAs) (Djodjic et al. 2002), which, because they represent high concentrations of nutrients or sediment yield rate or surface runoff amounts, are a priority in water quality treatment or management (Zadeh et al. 2007). The magnitude and spatial distribution of water quality variables simulated by hydrologic models have been used as indicators of NPS hotspots (Srinivasan et al. 2005; Pandey et al. 2009; Kalin et al. 2004; Niraula et al. 2012; Emili and Greene 2013). When SWAT is used, simulations at the HRU level are directly related to hotspot identification. However, the degree to which defining fewer HRUs using thresholds affects SWAT model variable prediction is presently unknown. Therefore, it is important to study the effects of HRU numbers on the simulation of on-land variables, the magnitude and spatial distribution of which significantly affect NPS hotspot identification and stormwater management decisions.

To address these two issues, this study examined how the variation in number of HRUs (basic calculation units) affects the magnitude and spatial distribution of simulated on-land variables and SWAT-identified NPS hotspots in an urban watershed. Four SWAT models were developed using different HRU thresholds but keeping all geographic and weather input the same. Selected SWAT models were also calibrated and analyzed. The analysis focused on four annual on-land variables—surface runoff, sediment yield, total nitrogen (N), and total (P) generated at the HRU level—and four daily in-stream variables—stream discharge, total sediment, total N, and total P. The results were used to determine how the number of HRUs affects SWAT simulations in general and NPS hotspot identification in particular.

This paper is organized as follows: First, a brief introduction of the study area and details of the study methods, model setups, variables of interest, and model evaluation criteria are presented. Next, the comparison results of model simulation and hotspot identification in and between calibrated anduncalibrated SWAT models are provided. Finally, conclusions are drawn and future work is outlined.

Materials and Methodology

Study Area

The analysis focused on the Watts Branch watershed, which occupies part of Prince George County, Maryland, and Washington DC (Fig. 1). Watts Branch is the largest tributary of the Anacostia River, and its effluents eventually flow into the Chesapeake Bay. The Watts Branch stream has a total length of approximately 6.4 km, and the watershed has a drainage area of 9.14 km^2 (U.S. EPA 2013). A USGS gauging station monitors discharge continuously near the outlet (Subbasin 9). Additional water quality samples were obtained and analyzed for total sediment, nitrogen, and phosphorus, in 12 storms, from 2006 to 2008, by the DC Department of the Environment (DCDOE). The watershed is heavily urbanized, with 85% urban residential land use and 32% impervious surface. The unpaved soil associations found in the watershed are deep and nearly level to steep, with well-drained soils (DCDOH 2003). The mean slope of the watershed is 8.6%. High levels of suspended solids (TSSs) and nonpoint source pollutants impair Watts Branch water quality and are believed to be caused by past urbanization (U.S. EPA 2013). Stream restoration projects have been conducted in the watershed, and researchers are now analyzing the area for NPS hotspots and selection of effective best management practices (BMPs) (Leisnham et al. 2013).

SWAT Model Setup

SWAT2012 (Neitsch et al. 2011) input files for the Watts Branch Watershed were prepared using the *ArcSWAT* extension to *ArcGIS* (Winchell et al. 2007). The 1 arc/s DEM (USGS 2014), which has a cell size of approximately 10×10 m, was used to delineate the stream network and separate the watershed into 21 subbasins. Hydrologic response units were defined as combinations of the 2006 National Land Cover Data database (USGS 2014) and the SSURGO soil survey database (USDA and NRCS 2014). Other input data included precipitation and daily temperature data (NOAA and NCEI 2014) from the weather station at Regan National Airport in Washington, DC (9 km from the watershed). Autoapplications of nitrogen and phosphorus were activated to simulate fertilizer application on lawns in urban residential land use areas. Four uncalibrated and three calibrated SWAT models were developed using various HRU definition thresholds (Table 1).

The SWAT_0_C, SWAT_5_C, and SWAT_10_C models were calibrated on daily stream discharge data from the USGS station (October 1, 2002, to September 30, 2012) and water quality grab samples, using the nonlinear parameter estimation package PEST (Doherty 2005), which has been widely used in hydrological model calibration. The three models were given the same adjustable parameters, initial values, parameter calibration range, observations, objective functions, and all other elements related to calibration. The parameters selected for calibration, based on the literature and sensitivity analysis (Gitau et al. 2008; Bracmort et al. 2006; Liu et al. 2013), were the following: soil evaporation compensation

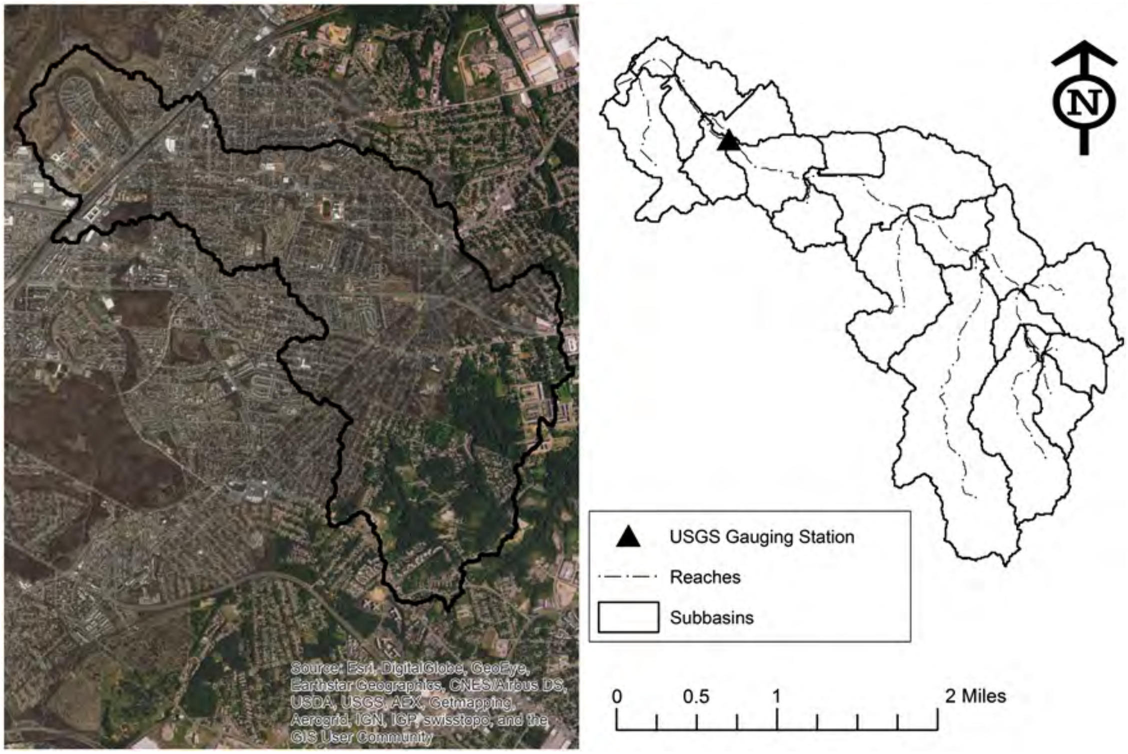

Fig. 1. Watts Branch watershed delineation (Map data from Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community)

Table 1. Summary of Calibrated/Uncalibrated SWAT Models

HRU definition thresholds[a]	0%–0%–0%	5%–5%–5%	10%–10%–10%	20%–20%–20%
Uncalibrated model	SWAT_0	SWAT_5	SWAT_10	SWAT_20
Calibrated model[b]	SWAT_0_C	SWAT_5_C	SWAT_10_C	[c]

[a]For land-use, soil-type, and slope.
[b]_C = calibration.
[c]SWAT_20 was not calibrated; it lost too much geographic information.

factor (ESCO), plant evaporation compensation factor (EPCO), nitrogen percolation coefficient (NPERCO), Manning's n value for tributary channels (N1), Manning's n value for main channels (N2), biological mixing efficiency (BIOMIX), USLE support practice factor (USLE_P), base flow recession factor (ALPHA_BF), and groundwater re-evaporation time (REVEP). To take into account the geographic differences in the watershed, the parameters were divided into subparameters grouped based on soil type, land use, and plant type. The grouping method was similar to that in Wang and Brubaker (2014).

SWAT Output Variables of Interest

Two groups of SWAT model outputs were analyzed in this study: in-stream variables and on-land variables. In-stream variables were stream discharge (m^3/s), sediment yield (t), total nitrogen (kg), and total phosphorus (kg) in effluent at the outlet of Subbasin 9. On-land variables were surface runoff (mm), sediment yield (t/ha), total N (kg/ha), and total P (kg/ha) contributed to streams from each HRU. In-stream variables were analyzed using daily averages, and on-land variables were analyzed using annual means. All variables of interest were compared among the two sets of models and also between the calibrated and uncalibrated models using the same number of HRUs. The in-stream variables were also compared with observations.

Statistical analysis was carried out on the observations and on the corresponding SWAT simulations. The evaluation criteria were correlation coefficient (r) and Nash-Sutcliffe coefficient (NSE), and biases were calculated for the period of October 1, 2002, to September 30, 2012, excluding a 2-year startup period.

The correlation coefficient, r, examines the linear relationship between observations and model simulations:

$$r = \frac{\sum_{i=1}^{n}(Q_m^i - \overline{Q_m})(Q_o^i - \overline{Q_o})}{\sqrt{\sum_{i=1}^{n}(Q_m^i - \overline{Q_m})^2}\sqrt{\sum_{i=1}^{n}(Q_o^i - \overline{Q_o})^2}} \tag{1}$$

where Q_m^i = ith predicted value; Q_o^i = ith observed value; n = number of observation; $\overline{Q_m}$ = mean value for all predicted values; and $\overline{Q_o}$ = mean value for all observations.

The Nash-Sutcliffe model efficiency coefficient, NSE, is used to assess the degree to which a model explains variations in observations (Nash and Sutcliffe 1970):

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Q_o^i - Q_m^i)^2}{\sum_{i=1}^{n}(Q_o^i - \overline{Q_o})^2} \tag{2}$$

Total and relative mean errors (biases) were used to quantify the fitness level between simulations and observations:

$$\bar{e} = \frac{\sum_{i=1}^{n} e_i}{n} = \frac{\sum_{i=1}^{n} (Q_m^i - Q_o^i)}{n} \quad (3)$$

$$\frac{\bar{e}}{\bar{Y}} = \frac{\sum_{i=1}^{n} e_i}{\sum_{i=1}^{n} y_i} = \frac{\sum_{i=1}^{n} (Q_m^i - Q_o^i)}{\sum_{i=1}^{n} Q_o^i} \quad (4)$$

The r, NSE, and bias values were calculated based on daily stream discharge at the gauging station for the 10-year simulation period. Also, NSE and biases were calculated for the in-stream water quality variables; however, because of their smaller sample size (12 samples over 3 years), the information they provided was more closely related to the order of magnitude of variations rather than to the long-term dynamics of sediments and nutrients.

Hotspot Identification and Run Time

Predictions of on-land variables by calibrated and uncalibrated SWAT models, with different HRU threshold levels, were used to identify hotspots of surface runoff, sediment yield, and nutrient generation in the Watts Branch watershed. The hotspots were defined as the top 20% of HRUs, ranked by the level at which they generate each constituent. Hotspots derived from the nonthresholded and calibrated model SWAT_0_C were used as a reference and were compared with those identified by the other models in terms of the percentage of watershed area that they occupy and the percentage of NPS that they generate. This was accomplished by mapping the top 20% of HRUs (hotspots), obtained from these other models, back onto the reference constituent generation maps and then calculating how much was generated by the reference model in those HRUs, which presumably overlap but do not coincide with the reference hotspots. The area and contribution of reference hotspot HRUs not identified by other models (missing hotspots) and the area and contribution of other models' hotspots not part of the reference (added hotspots) were also calculated to quantify the hotspot identification errors incurred by HRU-thresholded and uncalibrated models. As a final practical component, the times needed to calibrate and run the models on contemporary hardware were recorded. The hardware used was a quad-core Intel I-5 desktop (Dell, Austin, Texas).

Results and Discussion

Uncalibrated Models

The four uncalibrated models predicted similar stream discharges at the USGS gauging station (Table 2), with average daily values of approximately 0.126 m^3/s and standard deviation of 0.40 m^3/s. These uncalibrated predictions were also quite close to daily discharge observations (Fig. 2), with correlation coefficients better than 0.8 and NSEs of 0.52 to 0.60 indicating that the models explained more than 50% of observed flow variations (Table 2). Increasing the HRU definition threshold from 0 to 20% was observed to cause a 13% decrease in NSE, which indicated that the 0-threshold model was the best in terms of explained variance and a slight increase (10%) in standard deviations of predicted discharges. Theuncalibrated SWAT models also performed well in simulating stream discharge, which may suggest that hydrologic models, such as SWAT, can be more accurate with default parameter values in engineered (urban) watersheds with relatively more impervious areas. However, further study is needed to verify this statement by studying multiple study areas with various sizes, land uses, and watershed characteristics.

The four uncalibrated models predicted in-stream sediment yield statistics that increased by a factor of nearly 2 as the HRU threshold was increased from 0 to 20%. Mean sediment yield and standard deviation increased monotonically as the number of HRUs decreased because of the increased threshold levels. These

Table 2. Statistics for In-Stream Variables in the Uncalibrated SWAT Models

	Discharge (cms)					Sediment (t/day)		Total N (kg/day)		Total P (kg/day)	
Model	r	NSE	Rel. bias	Average	Std.	Average	Std.	Average	Std.	Average	Std.
SWAT_0	0.83	0.60	−0.1471	0.1250	0.40	109.58	741.09	12.76	21.72	12.1	80.16
SWAT_5	0.83	0.57	−0.1431	0.1256	0.42	132.59	859.36	12.46	21.23	12.24	77.66
SWAT_10	0.84	0.56	−0.1606	0.1263	0.43	155.47	978.85	12.05	20.56	12.11	75.9
SWAT_20	0.83	0.52	−0.1431	0.1256	0.44	213.33	1,267.75	11.35	20.45	12.74	77.91

Note: Rel. = relative; Std. = standard deviation.

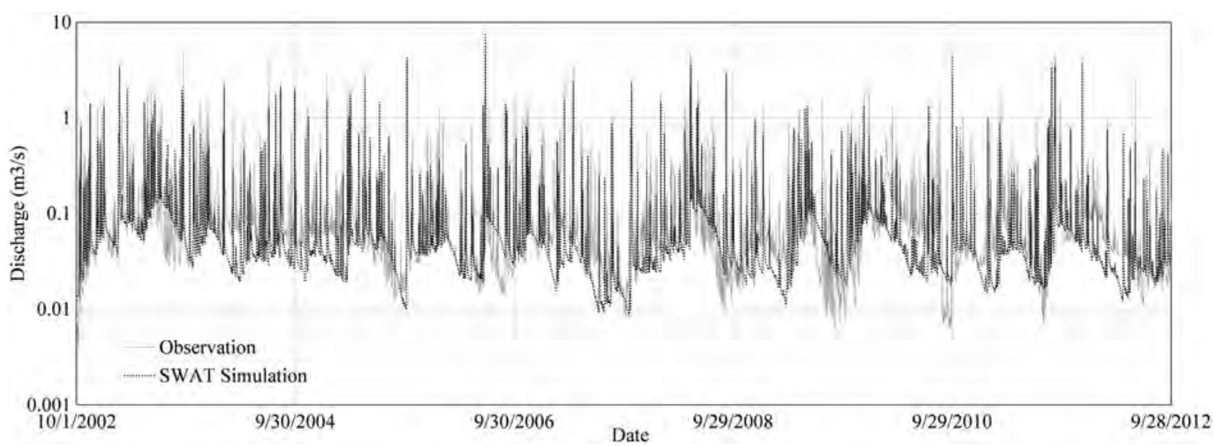

Fig. 2. Hydrographs of daily stream discharge observations and SWAT_0 simulations; the y-axis is in log scale for better visualization

results suggest that in the Watts Branch watershed the least frequently occurring UCs of soil, slope, and land use mostly generate below-average sediment levels. In this predominantly urban landscape, where over 85% of the watershed is residential and industrial and the mean slope is 8.6%, the eliminated UCs may have included parks, grassy areas, and zones of below average slope. The resulting increase in impervious surfaces and gradients (because eliminated UCs are replaced by dominant combinations in the thresholding process) leads to higher predicted surface runoff volumes and velocities along with increased sediment generation. However, increased surface runoff volumes may not be reflected in in-stream discharge levels (as observed here) because it is compensated by interflow. Notably, the doubling of predicted sediment yield in the uncalibrated models is caused by varying HRU definition thresholds only and does not reflect an actual change in watershed conditions.

In contrast to discharge predictions, the total in-stream N and P did not differ significantly between the four uncalibrated models (<10%). A mild, monotonic decrease in average and standard deviation of N was observed as the number of HRUs decreased, but no obvious trend was observed for total P. The reason may be that fertilized areas (e.g., parks, lawns) are eliminated by thresholding, as discussed previously, and by compensation of the decrease in applied P by increased sediment generation. The simulated N and P had similar average daily values but the simulated P had higher standard deviations compared with those of N. This outcome is reasonable because of the low mobility of P and its high correlation with sediment.

Statistics for on-land variables predicted by the uncalibrated models are summarized in Table 3, where the second column shows the number of HRUs in each model (from 1,832 at 0% threshold to just 109 at 20%), demonstrating how HRU thresholding resulted in Watts Branch models that are more computationally efficient. As the threshold level increased (and the number of HRUs decreased), these predictions followed mostly the same trends as for the in-stream variables but with possibly different magnitudes. Such results may be explained by the processes discussed earlier. The infrequently occurring UCs in this urban watershed correspond to areas that favor infiltration and generate below-average sediments; their elimination by thresholding causes more surface runoff and sediments to be predicted. The 20% increase in surface runoff (338 to 414 mm) was not reflected in discharge. Accordingly, an examination of in-stream variables alone was not sufficient to identify the presence of this on-land effect. The authors believe this effect to have been caused by interflow, whereby infiltrated water (in SWAT_0) contributed relatively quickly to stream flow (albeit more gradually than SWAT_20's surface runoff). Without calibration, this predicted increase in surface runoff was caused by varying HRU definition thresholds only and did not reflect a change in watershed conditions.

The spatial distribution of the annual mean surface runoff and sediment yield predicted by the uncalibrated models are shown in Fig. 3. The grey-to-black scales indicate increasing generation levels, whereas the white areas in the watershed boundaries represent HRUs with UCs eliminated by the thresholding process (in each subbasin, the area of missing HRUs is redistributed to the retained HRUs such that the entire watershed area continues to be represented in each model). Results with 0% HRU thresholding (SWAT_0) demonstrate how areas predicted to have high surface runoff generation (black) are localized and distributed in the watershed.

The figure also shows a main zone of high sediment yield in the northwestern quadrant of Subbasin 21, which coincides with above-average runoff generation. At the 5% HRU threshold level (SWAT_5), most of the eliminated UCs are observed to come from low runoff and sediment generation areas (light grey), mostly Subbasins 20 and 21. The hydrologic characteristics of these areas are replaced by those of neighboring areas (light grey to black) of the same subbasins by the thresholding process, leading to higher predicted surface runoff and sediments.

The process shown in Fig. 3 continues in the same direction at the 10 and 20% threshold levels, where, in the latter case, almost all light grey areas in the southeastern half of the watershed have been replaced by neighboring areas with above-average runoff and sediment generation. At the 20% level, the high sediment generating area in Subbasin 21 is preserved but now appears to cover the whole subbasin (neighboring white areas). Additionally, several localized high runoff generation areas, along with low runoff generation areas, have been replaced with intermediate runoff generation zones (grey) which This explains the smaller standard deviation of surface runoff discussed earlier. These effects are expected to limit the utility of the SWAT_20 model (in particular) in identifying runoff and sediment hot spots because it targets areas that are much larger in size.

Calibrated Models

Like the uncalibrated models, the three calibrated models predicted consistent stream discharges at the USGS gauging station (Table 4), but the calibrated average daily values were approximately 30% lower at 0.096 m^3/s. The observed consistency in discharge predicted by these models across varying spatial discretizations (HRU threshold levels here) agrees with the results of FitzHugh and MacKay (2000) and Jha et al. (2004). The calibrated models' predictions had correlation coefficients similar to those of the uncalibrated models but better NSEs of 0.65 (versus 0.52 to 0.60), indicating that the models explain nearly two-thirds of observed flow variations. These statistics were consistent across the HRU definition thresholds (0–10%). The 30% underestimation of stream discharge may not necessarily indicate an ineffective model calibration. The biases are attributed to all types of uncertainty, including errors in precipitation measurement and spatial variation in precipitation data.

The sediment yield predictions from the calibrated models differed substantially from those of the uncalibrated models. The in-stream daily sediment yield predicted by SWAT_0_C was 2.79 t/day, which is approximately 1/40 of the uncalibrated

Table 3. Statistics for On-Land Variables in the Uncalibrated SWAT Models

Model	Number of HRUs	Surface runoff (mm)		Sediment yield (t/ha)		Total N (kg/ha)		Total *P* (kg/ha)	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
SWAT_0	1,832	337.93	173.26	20.01	32.45	6.39	1.98	4.86	4.19
SWAT_5	740	355.03	161.78	29.67	43.39	6.25	1.72	4.96	3.30
SWAT_10	256	353.96	148.04	39.06	55.89	5.92	1.28	4.73	3.09
SWAT_20	109	414.39	117.50	49.70	65.81	5.95	1.26	4.65	3.01

Note: Std. = standard deviation.

prediction. The correlation coefficient was relatively low at 0.22, but the large decrease in magnitude demonstrates the importance of calibration for this variable even if the number of observed samples is small. In contrast to the uncalibrated models, here the predicted sediment yield decreased by half when the HRU threshold was increased to 10%, but it remained unmodified at 5%. This indicates that, although the calibration process modifies the hydrologic characteristics of all UCs toward lower sediment yields, it also leads some of the least frequently occurring UCs (removed between the 5 and 10% levels) to produce sediment loads above the new (much lower) average. Unlike the uncalibrated results, this suggests that the least occurring UCs represent a mixture of hydrologic conditions, including some that are particularly susceptible to erosion (e.g., uncovered soil).

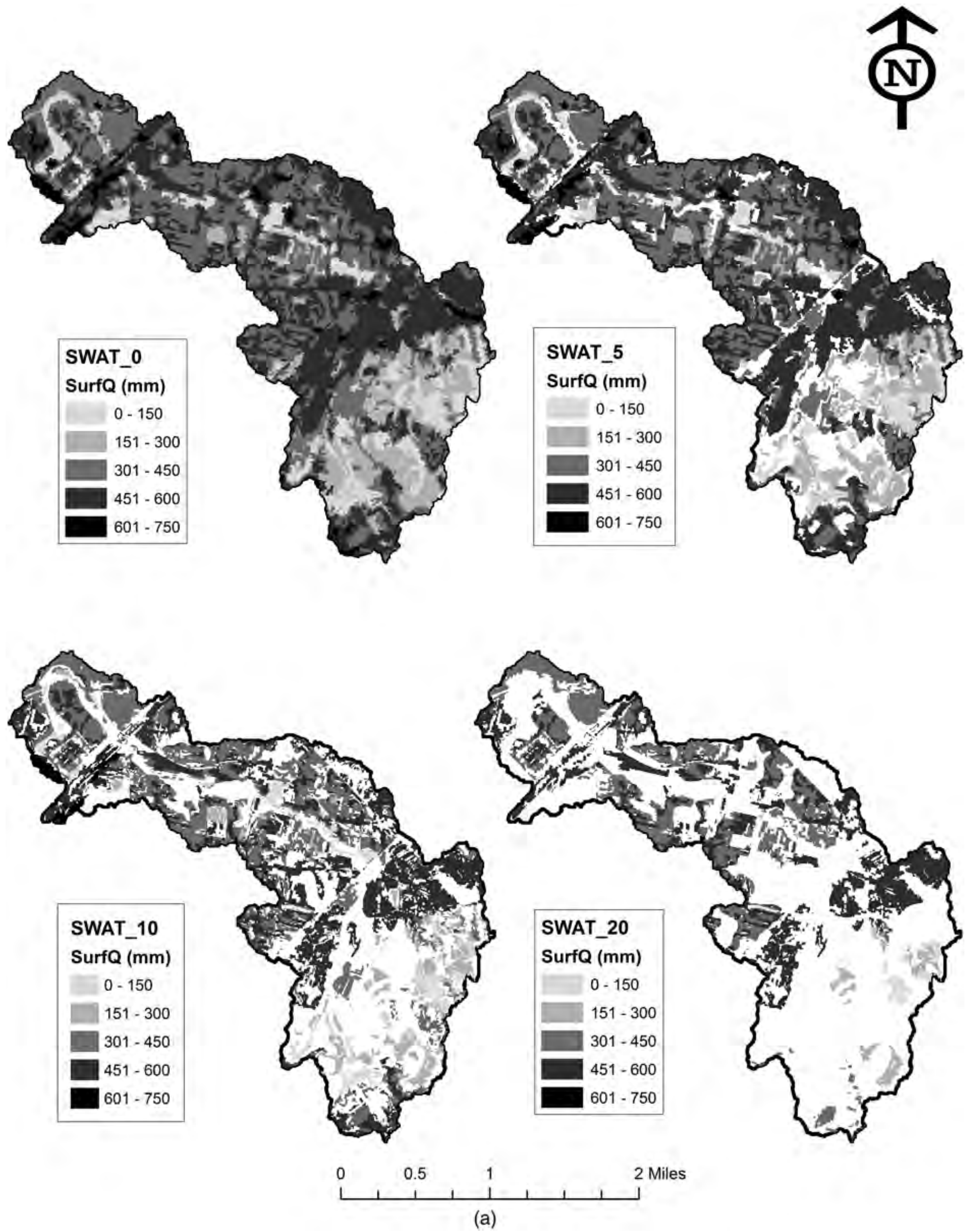

Fig. 3. (a) Spatial distributions of simulated surface runoff (mm) in uncalibrated models, with no HRU defined in the blank area; (b) spatial distributions of simulated sediment yield (t/ha) in uncalibrated models, with no HRU defined in the blank area

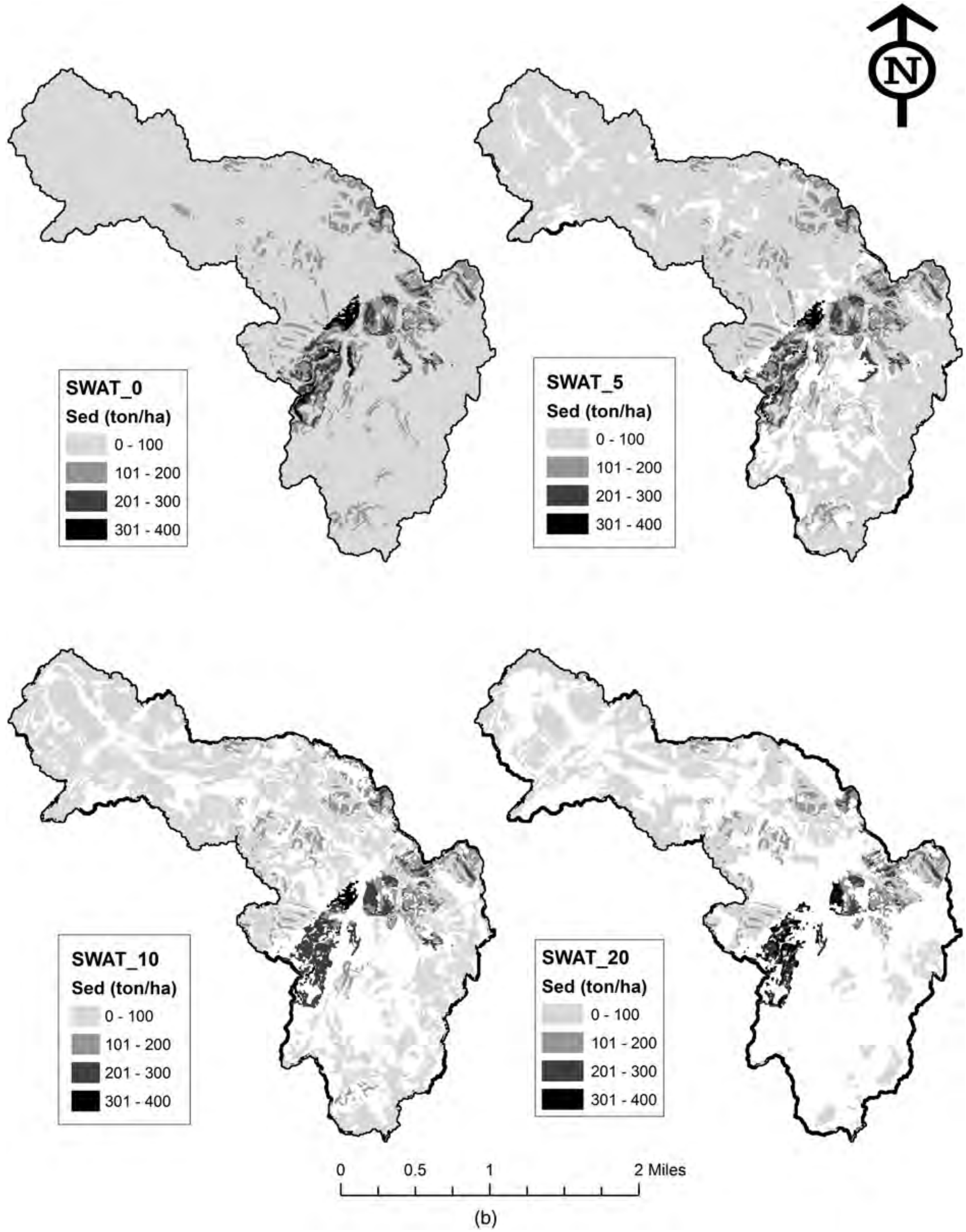

Fig. 3. (*Continued.*)

The mean predictions of the calibrated models for in-stream N were approximately 30% lower than the uncalibrated averages, where the phosphorus predictions were approximately 1/5 of the uncalibrated prediction. These calibrated means have similar values at the 0 and 5% HRU threshold levels and decrease at the 10% level by approximately 10 and 30%, respectively. A similar but more gradual decrease was also observed with the uncalibrated models, as discussed earlier. Overall, the uncalibrated models produced predictions of discharge and in-stream N that are quite similar to those of the calibrated models, with a magnitude within 30% of the calibrated results and similar trends in HRU threshold levels. Uncalibrated phosphorus and sediment yield predictions, however, change markedly with calibration.

Statistics for on-land variables predicted by the calibrated models are summarized in Table 5. The means and standard deviations for all variables decreased as the HRU threshold level increased to

Table 4. Statistics for In-Stream Variables in the Calibrated SWAT Models

Model	Discharge (m^3/s)				Sediment (t/day)		Total N (kg/day)		Total P (kg/day)	
	r	NES	Rel. bias	Average	*r*	Average	*r*	Average	*r*	Average
SWAT_0_C	0.82	0.65	−0.35	0.0960	0.22	2.79	0.88	8.96	0.65	2.43
SWAT_5_C	0.82	0.65	−0.36	0.0940	0.22	2.79	0.88	8.96	0.67	2.43
SWAT_10_C	0.83	0.66	−0.35	0.0951	0.22	1.35	0.88	8.14	0.65	1.62

Note: Rel. = relative.

Table 5. Statistics for On-Land Variables in the Calibrated SWAT Models

Model	Number of HRUs	Surface runoff (mm/year)		Sediment yield (t/ha/year)		Total N (kg/ha/year)		Total P (kg/ha/year)	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
SWAT_0_C	1,832	283.35	158.97	4.36	7.75	4.73	3.14	2.34	3.59
SWAT_5_C	740	279.56	143.38	1.94	3.16	4.59	2.77	1.44	1.97
SWAT_10_C	256	275.53	128.31	0.81	0.83	4.28	2.31	0.85	0.78

Note: Std. = standard deviation.

the 5 and 10% levels, indicating that in these calibrated models the least frequently occurring UCs include the largest contributors of surface runoff, sediment, and nutrients. The most important changes were for the mean sediment yield and phosphorus, which decreased by 79 and 65%, respectively, when the HRU threshold level went from 0 to 10% whereas runoff and N decreased by less than 10%.

Fig. 4 shows the spatial distribution of annual mean surface runoff, sediment yield, N, and P predicted on land by the calibrated models. The color scale is to be interpreted in the same way as in Fig. 3. The calibrated result for surface runoff is observed to be similar to that of the uncalibrated (SWAT_0) model, albeit with fewer high-intermediate areas (dark grey) but the result for sediment yield differs markedly. With calibration, localized zones of high sediment generation are observed to be distributed throughout the watershed rather than limited to Subbasin 21, and (as expected from a process-based perspective) are seen to be correlated with high runoff generation areas. These zones are drowned out by the uncalibrated overpredictions in Subbasin 21, which are 6 times larger than calibrated values. Phosphorus generation areas are further observed (as expected) to be correlated with runoff and sediment generation zones. Nitrogen production, on the other hand, is more broadly observed in the northern half of the watershed in zones of high and intermediate runoff generation, possibly corresponding to fertilized lawns. As with the uncalibrated models, HRU thresholding removed infrequently occurring UCs from the calibrated models; however, with calibration subbasins containing the low-generating UCs that were removed were also predicted to have a lower overall contribution than in the uncalibrated case. Accordingly, the removed low-contributing UCs were replaced by HRUs that had similar hydrologic characteristics, leading to little increase in annual on-land variables. The change in these variables (downward) was caused by the removed high-contributing (yet infrequently occurring) UCs, whose effect was no longer counterbalanced by the aggregation of low-contributing UCs in the calibrated models.

Hotspot Identification

The results of hotspot identification with the calibrated models are summarized in Table 6. For the reference model (SWAT_0_C), runoff hotspots occupy 20% of the watershed area but contribute 31% of the generated runoff. The coverage area and contribution percentages for sediment hotspots are 2 and 21%; for nitrogen hotspots, 16 and 32%; and for phosphorus hotspots, 4 and 22%. Targeting BMPs to these hotspots, if possible, would generate hydrologic benefits in ratios of approximately 1.5:1 for runoff, 2:1 for N, 5:1 for P, and 10:1 for sediment, relative to the implementation area. Runoff hotspots identified with HRU-thresholded models are observed to occupy less area than the reference but to maintain a similar benefit ratio relative to implementation area. These models miss reference hotspots in proportion to the threshold level, but do not identify extraneous non-hotspot areas. Implementing BMPs in these hotspots would reduce surface runoff less than in the reference hotspots but would cost less in near proportion. Results for nitrogen are quite similar to those for runoff, with near maintenance of the 2:1 ratio, but less area is targeted as HRU threshold levels increase. Also, the identified extraneous non-hotspot areas are small here. The situation is different for sediments and phosphorus, however. For these constituents, the hotspots identified with HRU thresholds occupy more area than the reference but simultaneously contribute less of the watershed-generated totals. The hotspots missed by the thresholded models contribute more sediments and phosphorus than do the hotspots added by these models; as a consequence, the benefit ratios drop (from 5:1 and 10:1) to approximately 2:1 at the 10% HRU threshold level. Applying sediment and phosphorus BMPs to the thresholded hotspots would still be beneficial, but would cost more and reduce these constituents less than if the reference hotspots were targeted.

The results of comparing hotspots identified by uncalibrated models and reference hotspots are summarized in Table 7. For surface runoff, the uncalibrated model without thresholding identifies more hotspot area than the reference, and the models with HRU thresholds identify fewer. However, the benefit ratio of the identified hotspots is nearly the same, 1.5:1, as for the calibrated model. This suggests that even extraneous hotspots are valid in this case. The situation is similar for nitrogen, with identified hotspots nearly identical in area and contribution to those of the reference model without thresholding, and to those of the HRU-thresholded calibrated models at the 5 and 10% levels. Results are not as promising for sediment yield and phosphorus generation. As one might expect from a comparison of Figs. 3(b) and 4(b), sediment hotspots are almost entirely misidentified by the uncalibrated models, leading to a benefit ratio of approximately 0.8:1 (nearly constant over HRU-thresholded levels). Accordingly, implementing sediment control BMPs in these misidentified hotspots would return less "bang for the buck" than would implementing BMPs over the entire watershed (which, by definition, has a 1:1 ratio of contribution to area).

Phosphorus hotspots identified by the uncalibrated models decrease in both area and contribution as the HRU-threshold level increases. At the 0% threshold, hotspots occupy 14% of the watershed area and contribute 28% of the generated phosphorus for a benefit ratio of 2:1, which matches the lowest hotspot identification performance of the calibrated models (SWAT_10_C) but targets a larger area. At the 10% threshold, however, phosphorus hotspots are entirely misidentified, leading to a 0.8:1 "benefit" ratio for BMP implementation.

Run Time Comparison

The computational times required to perform various parts of the analysis in this study are listed in Table 8. Daily run times, used for example in uncalibrated model simulations, are nearly proportional to the number of HRUs generated by the different HRU-thresholding levels, and they range from approximately 1 to 5 min. With such short run times, there is no real incentive to apply nonzero HRU thresholds to the uncalibrated models, especially because that can negatively affect the identification of phosphorus hot spots. Calibration times, however, range from 7 h to 8 days, which is 500 to 2,000 times longer than daily run times, depending on the applied HRU threshold. Such long times are required by the calibration software (PEST in this case) to adjust model parameters, rerun the model, and compute the objective function the hundreds of times needed to minimize prediction errors. These computational times are required only for the final calibration and do not include times required for prior calibration with alternative parameter sets and groupings that are eventually rejected but count against impending deadlines in a "real-world" project. For example, 20 trial calibrations

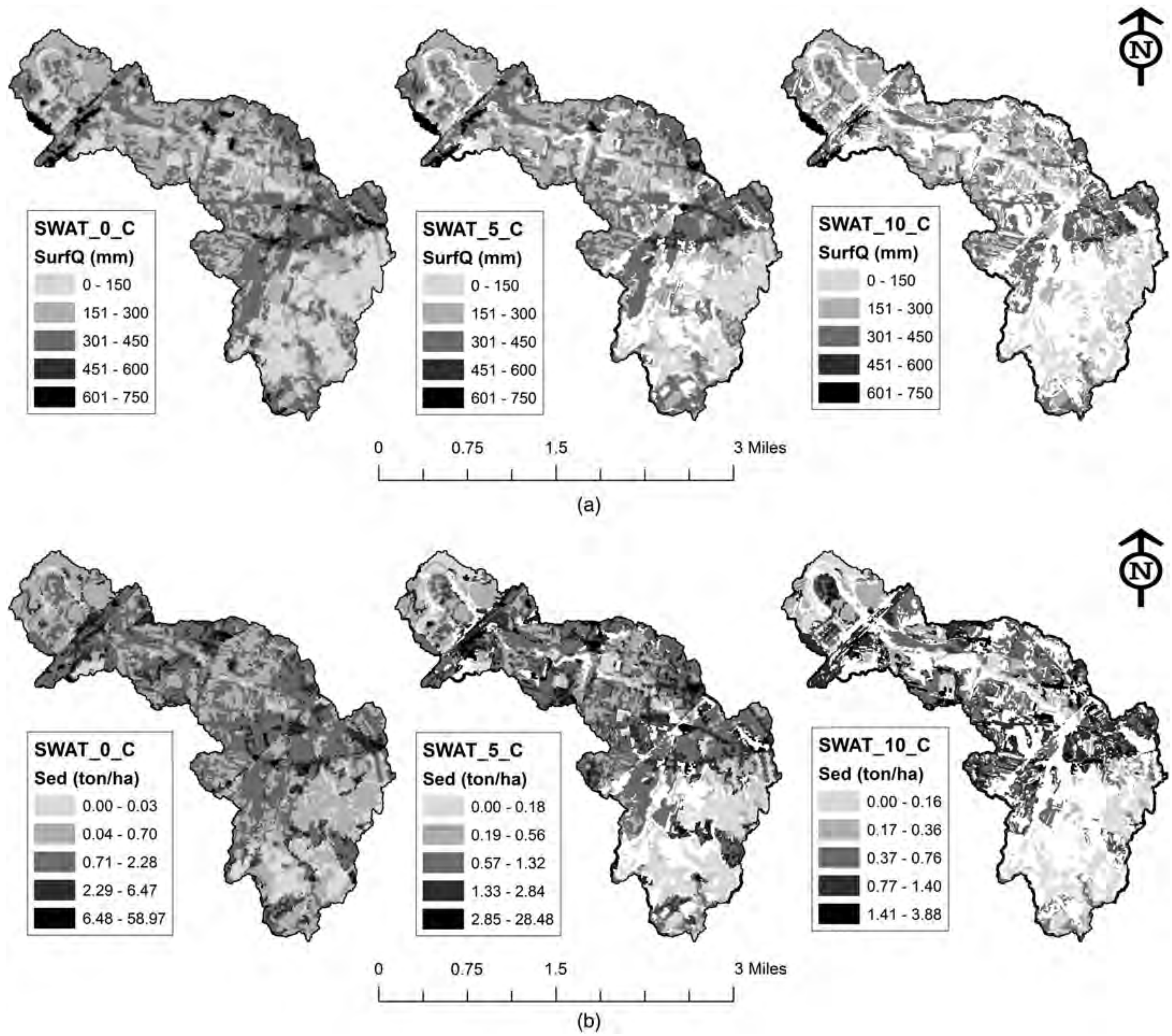

Fig. 4. (a) Spatial distributions of simulated surface runoff (mm) in calibrated models, with no HRU defined in the blank area; (b) spatial distributions of simulated sediment yield (t/ha) in calibrated models, with no HRU defined in the blank area; (c) spatial distributions of simulated total N yield (kg/ha) in calibrated models, with no HRU defined in the blank area; (d) spatial distributions of simulated total P yield (kg/ha) in calibrated models, with no HRU defined in the blank area

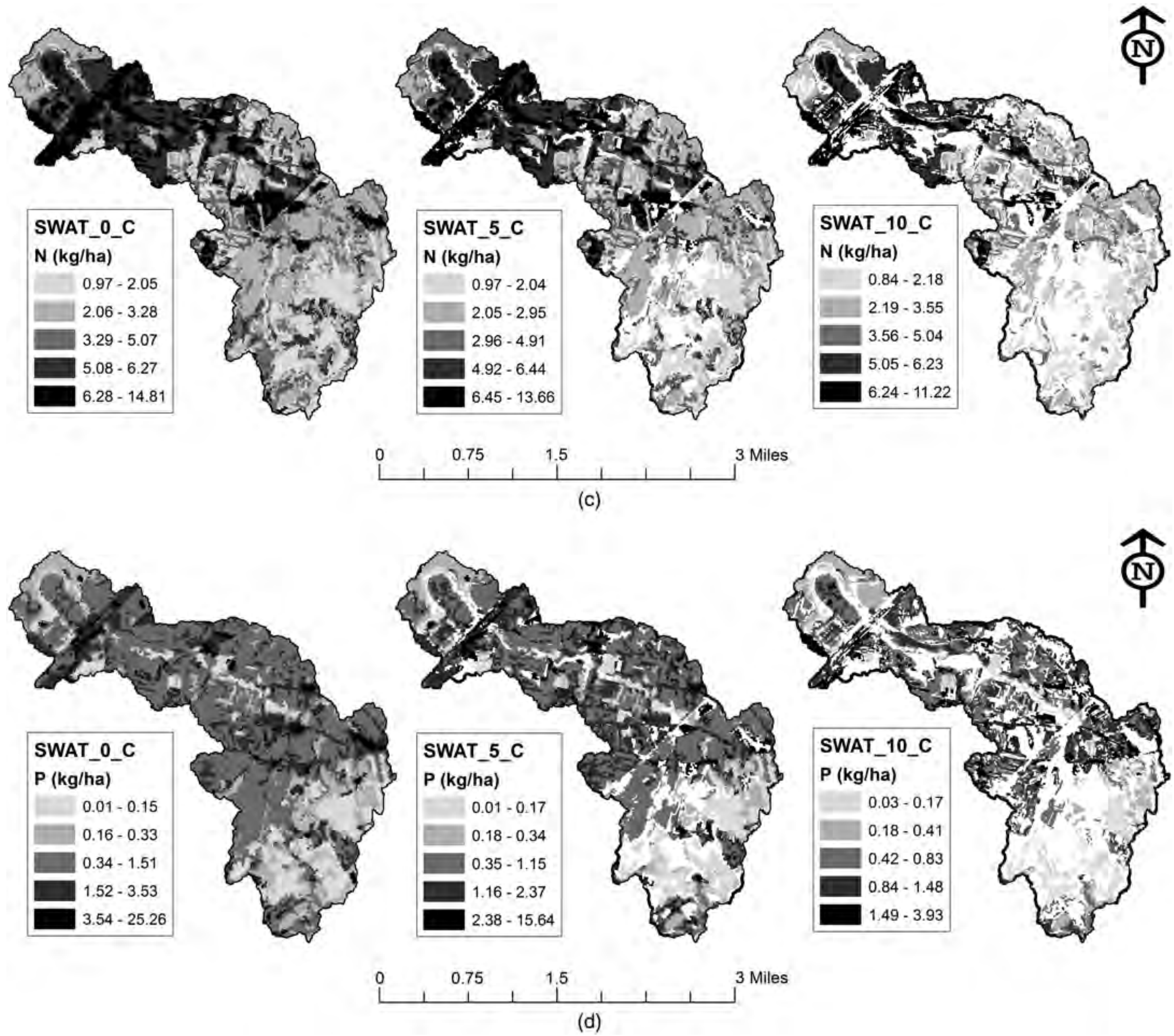

Fig. 4. (*Continued.*)

Table 6. HotspotDifferences in Calibrated Models (Area and Amount)

		Surface runoff (mm/year)			Sediment yield (t/ha/year)			Total N (kg/ha/year)			Total P (kg/ha/year)		
Top 20% HRU identified as hotspots		0-c	5-c	10-c	0-c	5-c	10-c	0-c	5-c	10-c	0-c	5-c	10-c
Hotspot identified	Watershed area (%)	19.51	15.56	11.38	2.35	4.60	5.16	15.85	13.81	10.05	4.22	6.16	6.91
	Total weight (%)	30.80	24.21	17.43	21.24	17.02	9.48	31.53	26.76	18.71	21.83	18.96	13.67
	B. ratio[a]	1.58	1.56	1.53	9.05	3.70	1.84	1.99	1.94	1.86	5.17	3.08	1.98
Missing hotspots	Watershed area (%)	—	3.95	8.13	—	1.84	2.35	—	2.40	6.54	—	2.51	3.92
	Total weight (%)	—	6.59	13.37	—	17.16	21.24	—	5.28	13.83	—	14.05	20.81
Added hotspots	Watershed area (%)	—	0.00	0.00	—	4.09	5.16	—	0.36	0.73	—	4.45	6.61
	Total weight (%)	—	0.00	0.00	—	12.94	9.49	—	0.51	1.01	—	11.18	12.64

Note: -c = calibrated models.
[a]Benefit ratio = weight percentage/area percentage.

require total model calibration times at (at best) 6 months, 2 month, or 2 weeks for HRU threshold levels of 0, 5, and 10%, respectively.

In the present study, the calibrated model with a 10% HRU threshold (SWAT_10_C) has an advantage over the much faster uncalibrated SWAT_0 model only for in-stream and on-land sediment predictions, which may not be sufficient to fully justify its use in any but the most time-constrained situations for which calibration data are available. A calibrated model should always be used

Table 7. Hotspots Difference in Uncalibrated Models (Area and Amount)

		Surface runoff (mm/year)			Sediment yield (t/ha/year)			Total N (kg/ha/year)			Total P (kg/ha/year)		
Top 20% HRU identified as hotspots		0	5	10	0	5	10	0	5	10	0	5	10
Hotspot identified	Watershed area (%)	24.27	18.98	12.96	39.65	27.07	16.36	16.42	14.06	9.91	14.46	13.37	9.74
	Total weight (%)	36.19	27.84	18.80	31.68	19.27	12.56	31.66	26.64	18.09	28.06	18.39	7.93
	B. ratio[a]	1.49	1.47	1.45	0.80	0.71	0.77	1.93	1.89	1.82	1.94	1.38	0.81
Missing hotspots	Watershed area (%)	5.29	9.47	12.94	2.22	2.35	2.35	0.49	2.46	6.54	2.10	3.60	4.22
	Total weight (%)	7.62	14.59	20.32	18.71	21.24	21.24	0.76	5.36	13.83	9.35	18.66	21.83
Added hotspots	Watershed area (%)	10.05	8.94	6.38	39.53	27.08	16.38	1.06	0.67	0.60	12.34	12.75	9.74
	Total weight (%)	13.01	11.63	8.32	29.16	19.35	12.63	0.90	0.47	0.39	15.58	15.22	7.93

[a]Benefit ratio = weight percentage/area percentage.

Table 8. Comparison of SWAT Runtime and Calibration Time

Model	Number of HRUs	Calibration (h)	Daily run (s)
0–0–0	1,832	191	352s
5–5–5	740	74	134s
10–10–10	256	7	47s

when calibration data are available, but applying a 10% HRU threshold to it does not justify the expense, time, and care involved in the flow monitoring, water sampling, and analysis required to produce these data. In the general case, it is best to use the calibrated 0-threshold modeling approach, although the calibrated model with 5% HRU thresholding is a middle-of-the-road alternative, with acceptable hotspot identification and calibration time.

Conclusions

In this study, the impact of HRU threshold values on predictions of in-stream and on-land variables by calibrated and uncalibrated SWAT models was investigated for a small urban watershed, Watts Branch, at the border between Maryland and Washington DC. HRU thresholds of 0, 5, and 10% were used with the calibrated models, and thresholds of 0, 5, 10, and 20% were used with the uncalibrated models.

Results indicate that calibrated models accurately predict daily stream discharge and nitrogen export at all tested HRU thresholds. Although the uncalibrated predictions of these variables are within 30% of the calibrated predictions in this study, model calibration was still needed to obtain sediment yield and phosphorus export predictions at the correct order of magnitude. For these in-stream variables, an increase in HRU threshold increased the predicted values in the uncalibrated models but decreased them in the calibrated models.

There was better agreement between calibrated and uncalibrated model predictions for on-land variables at the 0% HRU threshold, but uncalibrated sediment yield and phosphorus remained overpredicted. Additionally, discrepancies increased as the HRU threshold increased because this mostly led to a decrease in predicted values for the calibrated models whereas predicted values remained either relatively constant or increased for the uncalibrated models.

Spatial predictions of on-land variables, presented as maps, helped to explain the discrepancies in sediment yield predictions by the uncalibrated and calibrated models, and the variations in predictions (in opposite directions) with HRU thresholding. The main cause was found to be a small area of Subbasin 21, where default parameter values produced sediment yields that were 6 times higher than those produced with calibrated parameter values. This highlights the importance of model calibration, even with a limited data set, at least for sediment predictions.

The results for hotspot identification, where predictions of the calibrated model with a 0% HRU threshold were used as the reference, indicate that the only acceptable uncalibrated model is that with a 0% HRU threshold. However, this model was not suitable for identifying sediment generation hotspots; moreover, increasing the HRU threshold made it unsuitable for phosphorus hotspot identification. Calibrated models with 0–10% HRU thresholds were generally adequate for hotspot identification for the four studied constituent variables. However, the benefit ratios of identified sediment yield and phosphorus hotspots decreased as the HRU threshold increased for these models.

This research shows that defining HRUs with different thresholds can affect simulations of on-land hydrological processes. The simulated values and spatial distribution of on-land variables are especially important to NPS hotspot identification and NPS control. According to this research, for similar watersheds with available monitoring data, a model should be calibrated and the smallest HRU threshold allowed by the study's time frame should be used. The location of the hotspots, determined by the relative variable values, is more important than the absolute variable values. This is why uncalibrated models were analyzed in this study, the results of which suggest that for an ungagged watershed, where calibration is impossible, an uncalibrated model with a 0% HRU threshold is preferable because it runs relatively quickly and produces acceptable hotspot identifications for surface runoff, nitrogen, and phosphorus. These findings suggest that researchers should carefully consider HRU thresholds when stuying NPS and SWAT in small urban watersheds with edaphic and topographic characteristics similar to those of Watts Branch.

This study also demonstrated that the SWAT hydrologic model, which is commonly used in rural watersheds, can be successfully used in flow and water quality simulations in small urban watersheds. The GIS interface *ArcSWAT* provides a convenient way to prepare input data sets for the model and efficiently identify and geo-locate NPS pollution hotspots. Once the targeted areas are determined, appropriate structural and nonstructural BMPs, along with education and incentive programs, can be designed, implemented, and carried out to remedy hotspots with the highest resource efficiency (Leisnham et al. 2013). Accordingly, the application of this type of model, with the smallest HRU thresholds, is expected to significantly enhance the ability to efficiently control excessive runoff and NPS pollution in urban areas.

Acknowledgments

The authors thank USEPA for providing financial support (Grant Number: R835284). This work is part of the research project Sustainable Community Oriented Stormwater Management (S-COSM): A Sensible Strategy for the Chesapeake Bay, which

aims to efficiently improve urban stormwater conditions by increasing adoption of best management practices, specifically for targeted hotspots, via community-based participatory research. The authors also thank Stephen Reiling of the DC Department of the Environment for providing water quality data in the Watts Branch watershed.

References

Abbott, M. B., and Refsgaard, J. C., eds. (1996). *Distributed hydrological modeling*, Vol. 22, Springer.

Blöschl, G., and Sivapalan, M. (1995). "Scale issues in hydrological modelling: A review." *Hydrol. Processes*, 9(3–4), 251–290.

Bracmort, K. S., Arabi, M., Frankenberger, J. R., Engel, B. A., and Arnold, J. G. (2006). "Modeling long-term water quality impact of structural BMPs." *Trans ASABE*, 49(2), 367–374.

Brown, D. G., Bian, L., and Walsh, S. J. (1993). "Response of a distributed watershed erosion model to variations in input data aggregation levels." *Comput. Geosci.*, 19(4), 499–509.

Chaplot, V. (2005). "Impact of DEM mesh size and soil map scale on SWAT runoff, sediment, and NO_3-N loads predictions." *J. Hydrol.*, 312(1), 207–222.

Chaubey, I., Cotter, A. S., Costello, T. A., and Soerens, T. S. (2005). "Effect of DEM data resolution on SWAT output uncertainty." *Hydrol. Processes*, 19(3), 621–628.

DC Department of Health. (2003). "Final total maximum daily loads for total suspended solids in watts brach." ⟨http://green.dc.gov/sites/default/files/dc/sites/ddoe/publication/attachments/zfin_tmdl_tss_watts.pdf⟩ (Aug. 2013).

Djodjic, F., Montas, H., Shirmohammadi, A., Bergström, L., and Ulén, B. (2002). "A decision support system for phosphorus management at a watershed scale." *J. Environ. Qual.*, 31(3), 937–945.

Doherty, J. (2005). *PEST: Model independent parameter estimation*, 5th Ed., Watermark Numerical Computing, Brisbane, Australia.

Dutta, D., and Nakayama, K. (2009). "Effects of spatial grid resolution on river flow and surface inundation simulation by physically based distributed modelling approach." *Hydrol. Processes*, 23(4), 534–545.

Emili, L. A., and Greene, R. P. (2013). "Modeling agricultural nonpoint source pollution using a geographic information system approach." *Environ. Manage.*, 51(1), 70–95.

FitzHugh, T. W., and Mackay, D. S. (2000). "Impacts of input parameter spatial aggregation on an agricultural nonpoint source pollution model." *J. Hydrol.*, 236(1), 35–53.

Gitau, M. W., Gburek, W. J., and Bishop, P. L. (2008). "Use of the SWAT model to quantify water quality effects of agricultural BMPs at the farm-scale level." *Trans. Am. Soc. Agric. Biol. Eng.*, 51(6), 1925–1936.

Hessel, R. (2005). "Effects of grid cell size and time step length on simulation results of the Limburg soil erosion model (LISEM)." *Hydrol. Processes*, 19(15), 3037–3049.

Jha, M., Gassman, P. W., Secchi, S., Gu, R., and Arnold, J. (2004). "Effect of watershed subdivision on SWAT flow, sediment, and nutrient predictions." *J. Am. Water Resour. Assoc.*, 40(3), 811–825.

Kalin, L., Govindaraju, R. S., and Hantush, M. M. (2003). "Effect of geomorphologic resolution on modeling of runoff hydrograph and sedimentograph over small watersheds." *J. Hydrol.*, 276(1), 89–111.

Kalin, L., Govindaraju, R. S., and Hantush, M. M. (2004). "Development and application of a methodology for sediment source identification. I: Modified unit sedimentograph approach." *J. Hydrol. Eng.*, 10.1061/(ASCE)1084-0699(2004)9:3(184), 184–193.

Kuo, W. L., et al. (1999). "Effect of grid size on runoff and soil moisture for a variable-source-area hydrology model." *Water Resour. Res.*, 35(11), 3419–3428.

Leisnham, P., et al. (2013). "Watershed diagnostics for improved adoption of management practices: Integrating biophysical and social factors across urban and agricultural landscapes." *ASABE Annual Int. Meeting*, American Society of Agricultural and Biological Engineers, St. Joseph, MI.

Liu, R., Zhang, P., Wang, X., Chen, Y., and Shen, Z. (2013). "Assessment of effects of best management practices on agricultural non-point source pollution in Xiangxi River watershed." *Agric. Water Manage.*, 117, 9–18.

Mamillapalli, S., Srinivasan, R., Arnold, J. G., and Engel, B. A. (1996). "Effect of spatial variability on basin scale modeling." *Proc., 3rd Int. Conf./Workshop on Integrating GIS and Environmental Modeling*, National Center for Geographic Information and Analysis, Santa Barbara, CA.

Nash, J., and Sutcliffe, J. V. (1970). "River flow forecasting through conceptual models. IA: Discussion of principles." *J. Hydrol.*, 10(3), 282–290.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., and Williams, J. R. (2011). *Soil and water assessment tool: Theoretical documentation, version 2009*, Texas A&M Univ. System, College Station, TX.

Niraula, R., Kalin, L., Wang, R., and Srivastava, P. (2012). "Determining nutrient and sediment critical source areas with SWAT: Effect of lumped calibration." *Trans. ASABE*, 55(1), 137–147.

NOAA and NCEI (National Oceanic and Atmospheric Administration and National Centers for Environmental Information). (2014). "Map viewer." ⟨https://gis.ncdc.noaa.gov/maps/ncei/⟩ (Aug. 2014).

Panagopoulos, Y., Makropoulos, C., and Mimikou, M. (2012). "Decision support for diffuse pollution management." *Environ. Modell. Software*, 30, 57–70.

Pandey, A., Chowdary, V. M., Mal, B. C., and Billib, M. (2009). "Application of the WEPP model for prioritization and evaluation of best management practices in an Indian watershed." *Hydrol. Processes*, 23(21), 2997–3005.

Romanowicz, A. A., Vanclooster, M., Rounsevell, M., and La Junesse, I. (2005). "Sensitivity of the SWAT model to the soil and land use data parametrisation: A case study in the Thyle catchment, Belgium." *Ecol. Modell.*, 187(1), 27–39.

Singh, V. P., and Frevert, D. K., eds. (2010). *Watershed models*, CRC Press, Boca Raton, FL.

Srinivasan, M. S., Gérard-Marchant, P., Veith, T. L., Gburek, W. J., and Steenhuis, T. S. (2005). "Watershed scale modeling of critical source areas of runoff generation and phosphorus transport." *J. Am. Water Resour. Assoc.*, 41(2), 361–377.

USDA and NRCS (Natural Resources Conservation Service). (2014). "Web soil survey." ⟨http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm⟩ (Aug. 2014).

U.S. EPA. (2013). "Restoration effects stabilize watts branch and reduce sediment loading." ⟨http://water.epa.gov/polwaste/nps/success319/upload/dc_watts.pdf⟩ (Aug. 2013).

USGS. (2014). "National map viewer." ⟨http://viewer.nationalmap.gov/launch/⟩.

Vieux, B. E., and Needham, S. (1993). "Nonpoint-pollution model sensitivity to grid-cell size." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(1993)119:2(141), 141–157.

Wang, Y., and Brubaker, K. (2014). "Implementing a nonlinear groundwater module in the soil and water assessment tool (SWAT)." *Hydrol. Processes*, 28(9), 3388–3403.

Winchell, M., Srinivasan, R., DiLuzio, M., and Arnold, J. (2007). "ArcSWAT interface for SWAT2005." ⟨http://www.geology.wmich.edu/sultan/5350/Labs/ArcSWAT_Documentation.pdf⟩ (Aug. 2013).

Zadeh, K. S., Montas, H. J., Shirmohammadi, A., Sadeghzadeh, A., and Gudla, P. R. (2007). "A diagnosis-prescription system for nitrogen management in environment." *J. Environ. Sci. Health Part A*, 42(5), 557–565.

Zhang, W., and Montgomery, D. R. (1994). "Digital elevation model grid size, landscape representation, and hydrologic simulations." *Water Resour. Res.*, 30(4), 1019–1028.