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Hourly Analyses of Hydrological and Water Quality Simulations Using the ESWAT Model

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Abstract Detailed analyses of hydrological and water quality variables are very important to study the dynamic processes in a river basin. In this study, we have further modified the Enhanced Soil and Water Assessment Tool (ESWAT) model by incorporating hourly evapotranspiration and overland flow routing modules. Results from comparison of the performances by two ESWAT versions indicate that the modified version performed better than the original model. The modified ESWAT model has reasonably reproduced observed time series runoff and most commonly collected water quality data. In addition, input data availability at required spatial and temporal resolutions is the major bottleneck in implementing many detailed hydrological models. In this paper, we have also developed a robust methodology to successfully disaggregate daily rainfall data into hourly datasets. Furthermore, we have assessed the implications of such daily rainfall disaggregation schemes on subsequent simulation of hydrological and water quality variables at river basin level. The outcomes suggest that the multivariate rainfall disaggregation scheme better reproduced observed rainfall and runoff data.

Keywords ESWAT · Multivariate · Rainfall disaggregation · RWQM · SWAT

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1 Introduction

Detailed analyses of hydrological and water quality variables are very important to manage environmental health in a river basin. However, not many models are available to reproduce both water quality and hydrodynamic variables at required spatial and temporal scales. Many models in the field of civil engineering, such as HEC-RAS, RIVER-2D and CH3D emphasize on the hydraulic part of the problem. On the other hand, models such as WASP, CE-QUAL-W2 and EPDRIV1 emphasize on the simulation of hydrodynamic and water quality variables in larger waterbodies, such as large rivers, reservoirs and lakes without making any reference to the processes in the upland watershed. Unfortunately, the majority of water quality problems emanate from upstream agricultural and residential areas. The latest National Water Quality Inventory (US EPA 2000) indicates that agriculture is the leading contributor to water quality impairments in the US, degrading 60% of the impaired river miles and half of the impaired lake acreage surveyed by states, territories, and tribes. This reinforces the need for the development of hydrological and water quality models that can successfully simulate both hydrodynamic and water quality variables at required temporal and spatial resolutions in the upstream watershed and riverine system combined.

The Soil and Water Assessment Tool (SWAT) model (Arnold et al. 1996; Neitsch et al. 2001) is a compromise between the spatial and temporal characteristics needed to monitor and manage environmental health within the basin. SWAT is a widely applied and proven public domain model used to manage the health of a watershed, and hence water quality. Many modifications have been introduced since its inception in terms of enabling the model to mimic observed field conditions spatially and temporally. One of the major changes was made by Van Griensven (Vandenberghe et al. 2001; Van Griensven et al. 2001; Van Griensven and Bauwens 2003) who called it the Enhanced SWAT (ESWAT) model. The ESWAT model facilitates hydrological and water quality simulations on an hourly basis in addition to other advantages, such as auto-calibration and parameters' sensitivity analysis. Also, the ESWAT model has addressed many limitations reported by the International Association of Water Quality task group on QUAL2E for river water quality processes (Henze et al. 1995; Masliev et al. 1995; Shanahan et al. 1998; Reichert et al. 2001). Masliev et al. (1995), Fronteau et al. (1999) and Shanahan et al. (1998) conducted a comparative analysis of activated sludge model and QUAL2E equations to create a river water quality model (RWQM) that can be used in an integrated urban modeling. They concluded that QUAL2E was poorly appropriate for this purpose. Some of the critics with QUAL2E include (after Masliev et al. 1995; Shanahan et al. 1998, 2001): (1) Failure to close mass balances involving interaction of the sediments; (2) Pelagic bacteria are not considered; (3) Lack of sessile microbiota; (4) Lack of different rates of hydrolysis and settlement for various organic fractions; and (5) Use of a biological oxygen demand (BOD) as a measure of organic carbon. Using BOD as a measure of organic carbon is hard to handle as it is not a quantitative mass value but only has a biological meaning (Masliev et al. 1995). BOD is also harder to estimate, compared to chemical oxygen demand.

Most of the drawbacks mentioned above with respect to QUAL2E are addressed in the RWQM (Rauch et al. 2002). Van Griensven (2002) incorporated the RWQM methodology into ESWAT, and one can choose to use either QUAL2E (Brown and Barnwell 1987) or RWQM (Rauch et al. 2002) to simulate in-stream water quality processes. She also made thorough analyses of comparisons between the performances by QUAL2E and RWQM, but failed short of conclusion due to comparable results by both models. However, she argues that, from theoretical viewpoint, the RWQM is well founded and should be used instead of QUAL2E in integrated urban river water quality modeling.

Although the current ESWAT model version performs hydrological and water quality simulations on hourly bases, there is still room available for improvement. ESWAT assumes that diurnal evapotranspiration and temperature distributions (influential forces in hydrological and water quality processes) are uniform. For example, hourly ET is computed by equally dividing the daily ET amount over 24 h. Similarly, ESWAT assumes that hourly average temperature is the same as average daily temperature, which will have a significant implication on algae activity that can subsequently play a significant role determining river water quality (e.g., photosynthesis, respiration, combined sewer overflows, etc.). Another drawback with the current ESWAT modeling approach is the lack of spatial connectivity of hydrologic response units (HRUs) in each sub-basin to one another or to the main channel, and hence one cannot explicitly indicate the HRUs that are directly connected to the main channel and that are not. Currently ESWAT assumes that all HRUs are directly connected to the main channel in the subbasin, and thus contribute runoff and pollutant loads directly, which is not always true—some HRUs are connected to the main channel of the subbasin through other HRUs, which requires an overland flow routing or some sort of time convolution to properly mimic the reality.

In addition to developing robust and yet detailed hydrological and water quality models, we also recognize that input data availability at required timescales is one of the major constraints in applying these and similar models (Socolofsky et al. 2001; Ireson et al. 2006; Holvoet et al. 2007). Precipitation and evapotranspiration (ET) are the major driving forces in any hydrological modeling (Abulohom et al. 2001; Mishra et al. 2007; Cao et al. 2008). Therefore, the objectives of this work were to: (1) modify the original ESWAT model by including hourly ET and overland flow routing modules and evaluate their consequent effects on hydrological and water quality simulations, and (2) develop a robust methodology that successfully disaggregates daily rainfall data into hourly datasets and evaluate the implications of such rainfall disaggregation schemes on subsequent hydrological and water quality processes. Objective 2 is specifically designed to make a better use of the largely available daily precipitation data in the study areas to provide the much needed hydrological and water quality information at hourly timescales. Although our study focuses on river basins in Texas, the same procedures could also be applied elsewhere.

1.1 The Study Areas

We used data from the Cedar Creek and Upper Trinity watersheds to examine the applicability of daily rainfall disaggregation schemes and the modified ESWAT model. Both the Cedar Creek and Upper Trinity watersheds are located in the Trinity River basin at the northeastern part of the State of Texas (Figs. 1 and 2). According to the geographic boundaries for SCS rainfall distributions, the watersheds are located within type III rainfall distribution (US SCS 1986). The major land use/ land cover

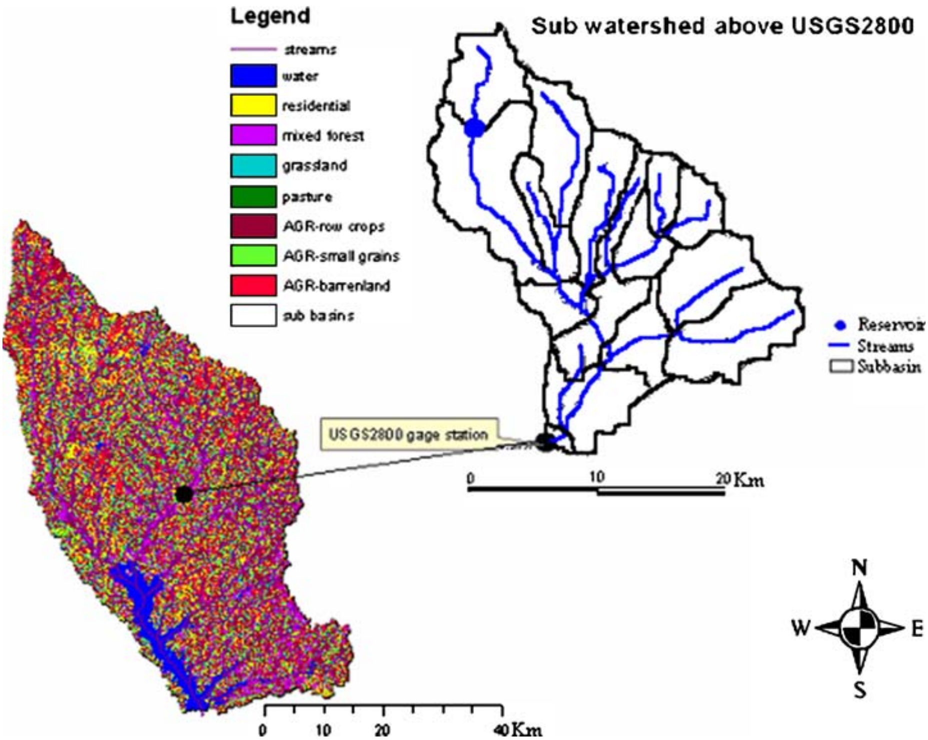

Fig. 1 Land use/land cover map and stream network of the Cedar Creek watershed

in the Cedar Creek watershed is agriculture (64%) followed by forest (12%) and residential (11%). Similarly, the major land use category in the Upper Trinity basin is agriculture (58%), followed by pastureland (21%) and forest (16%) (Figs. 1 and 2; Table 1). The Cedar Creek watershed feeds into Cedar Creek Reservoir (Fig. 1). Excess nutrient and sediment loads are the major water quality problems in the Cedar Creek reservoir. The algae blossoms due to excess phosphorus and other nutrients' loads is a major concern in the reservoir water quality (Ernst 2004—personal communication). General characteristics of the watersheds are also given in Table 2.

1.2 Input Data

1.2.1 Weather Data

Table 3 shows the sources of input data used in this study. Similarly, Table 4 depicts the temporal resolution of measured data; length of years of data availability; and number of gauge stations from where rainfall, runoff and water quality data were used. We checked the primary precipitation data for errors, and missing values were replaced by running a separate weather generator (WXGEN: Sharpley and Williams 1990). To make use of the largely available daily precipitation data in the watersheds (Table 4), the daily amounts were further disaggregated into hourly

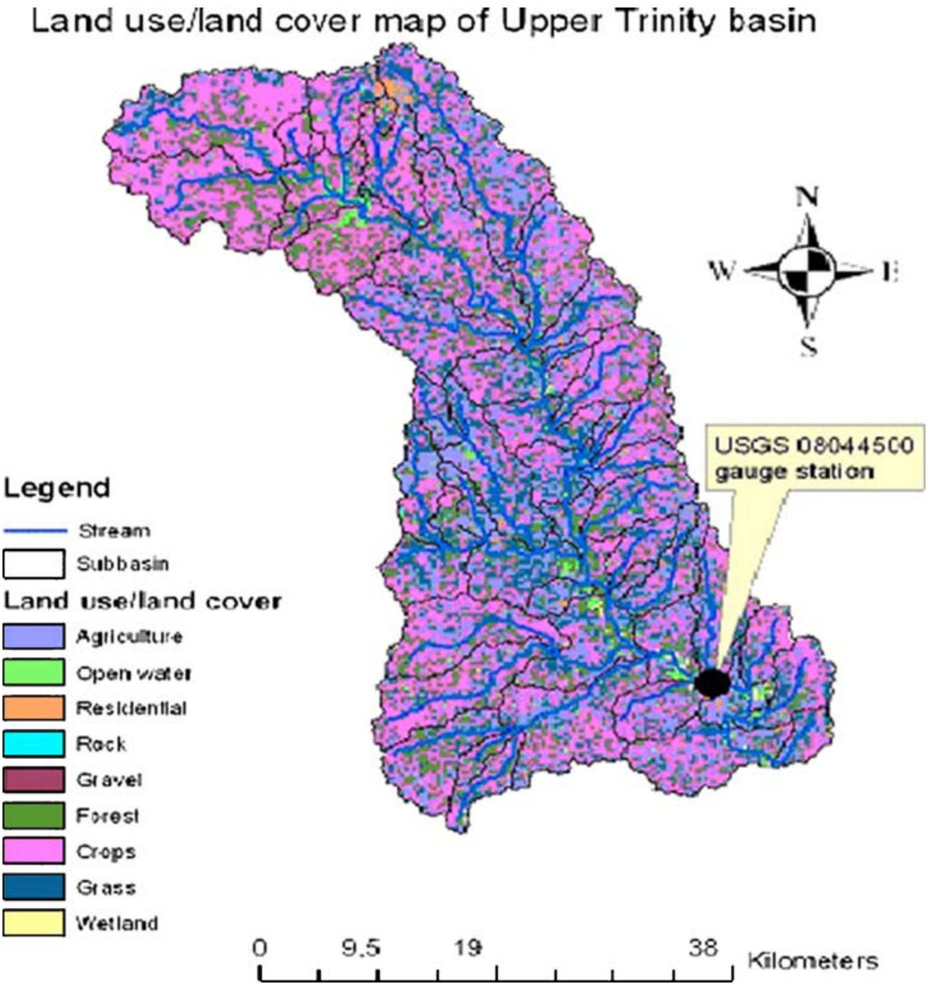

Fig. 2 Land use/land cover and stream network of the Upper Trinity watershed

dataset following: (a) uniform, (b) univariate, and (c) multivariate disaggregation schemes. The univariate disaggregation method focuses only on temporal stochastic rainfall disaggregation while the multivariate disaggregation scheme uses available

Table 1 Land use/land cover distribution by area in the Cedar Creek and Upper Trinity watersheds

Cedar Creek watershed		Upper Trinity watershed	
Land use/land cover type	Area [%]	Land use/land cover type	Area [%]
Water	6.38	Water/wetland	2.1
Urban	10.89	Residential	0.9
Forest	11.91	Forest	16.4
Rangeland/pastureland	6.81	Rangeland/grass	21.0
Agriculture	63.97	Agriculture	59.4

Table 2 General descriptions of the Cedar Creek and Upper Trinity watersheds

Watershed	Cedar Creek	Upper Trinity
Mean annual RF (mm)	1,018.1 (25 year)	676.3 (5 year)
Mean annual runoff (10^6 m^3)	99.09 (25 year)	212.8 (5 year)
Basin area[a] (km^2)	504.8	1,663.0

[a]Drainage area contributing runoff to the outlets at respective USGS stations (USGS2800 for Cedar Creek and USGS08044500 for Upper Trinity basin)

hourly rainfall distribution from the nearby weather stations and turns the spatial correlation that exists between precipitation data at pilot stations (stations with hourly precipitation records) and other gauge stations (stations where only daily rainfall data exist) to its advantage. Conversely, the uniform rainfall distribution approach assumes that hourly rainfall distribution is uniform—daily rainfall amount divided by 24. Daily maximum and minimum temperatures for the same length of years (25 years in the Cedar Creek and 5 years in the upper Trinity basins) were distributed over 24 h following the sinusoidal relationship (Neitsch et al. 2001; Debele et al. 2007). Missing and unavailable daily weather data values (e.g., for wind speed and relative humidity) were generated by running a separate weather generator model (WXGEN: Sharpley and Williams 1990). Daily wind speed and relative humidity data were distributed over 24 h using methods described in Waichler and Wigmosta (2003) and Debele et al. (2007), and were used in hourly ET calculations.

1.2.2 Soils and Land Use/Land Cover Data

Sources of data for soils, land use/land cover, and digital elevation model (DEM) are shown in Table 3. The DEMs were used for determining flow direction and accumulation, and stream network generation. The soils and land use/land cover data were overlaid to form distinct hydrologic units called Hydrologic Response Units. These HRUs were used as units of computation for upland hydrologic and water quality processes.

Table 3 Sources of input data for the Cedar Creek and Upper Trinity watersheds

Data type	Sources
Soils	http://www.ncgc.nrcs.usda.gov/products/datasets/statsgo/data/index.html (STATSGO—1:250,000)
Land use/land cover	http://www.mrlc.gov/zones/zones_info.asp (NLCD—30 m horizontal grid)
Topography	http://data.geocomm.com/catalog/US/sublist.html (DEM—1:24,000)
Weather data	http://lwf.ncdc.noaa.gov/oa/ncdc.html (NCDC—precipitation, temperature, solar radiation, relative humidity)
Stream flow	http://waterdata.usgs.gov/nwis/rt (USGS—daily stream flows at the gauge stations)
Water quality	http://www.epa.gov/storet/dbtop.html (EPA—most commonly collected water quality data)

Table 4 Number of gauge stations and length of years of input data used at different time-steps for rainfall, runoff and water quality at Cedar Creek and Upper Trinity watersheds

Watershed name	Rainfall		Runoff		Water quality
	Hourly	Daily	Hourly	Daily	Weekly/bi-weekly
Cedar Creek	2[a]	9[a]	1[a]	1[a]	1[a]
	1997–2001	1963–1987	1997–2001	1963–1987	1997–2001
Upper Trinity	4[a]	14[a]	1[a]	1[a]	N/A
	1999–2003	1999–2003	1999–2003	1999–2003	N/A

[a]Number of gauge stations from where rainfall, runoff and water quality data were obtained

1.2.3 Runoff and Water Quality

Hourly runoff data at USGS 08044500 (Upper Trinity, Fig. 2), and daily runoff data and grab sample water quality data at USGS2800 (Cedar Creek, Fig. 1) were available for our model parameters' calibrations (Table 4). Water quality data (sediments and nutrients) from grab samples were available for the Cedar Creek watershed on weekly (sometimes bi-weekly) basis. We used the LOADEST2 program (Runkel et al. 2004; White and Chaubey 2005) to generate daily water quality data. The LOADEST2 program was first trained with measured water quality and flow datasets at weekly timescales, and the trained model was later used to generate daily water quality data based on corresponding daily flow data (readers are referred to Runkel et al. (2004) for more information regarding the LOADEST2 program and the underlying theory).

2 Approaches

2.1 Rainfall Disaggregation

2.1.1 Univariate Rainfall Disaggregation

Building on our previous work (Debele 2005; Debele et al. 2007) and simplifying the more complex procedures in similar studies, we developed a robust procedure to stochastically disaggregate daily rainfall data into hourly data at a single station. We used the following assumptions and procedures to disaggregate daily rainfall data into hourly distributions using a univariate approach:

1. There is only one storm in a day. Similar assumptions have been successfully used in rainfall distribution studies in the US (Hershfield 1961; Frederick et al. 1977; Hershernhorn and Woolhiser 1987);
2. Storm beginnings follow a uniform distribution over 24 h. Debele (2005) from his study on daily rainfall disaggregation methods in the Cedar Creek watershed reported that over the years, rainfall contributed by each hour of the day follows a uniform distribution. Assumption of Poisson distributions to characterize storm beginnings has also been used in different rainfall distribution studies (Koutsoyiannis and Onof 2001);

3. Storm durations follow a two-parameter gamma distribution; and,
4. Storm intensity can be chosen to follow either of the methods (exponential or gamma distribution) based on rainfall intensity distributions in the area.

We developed a methodology to generate a unit hyetograph that would serve just like a unit hydrograph in runoff calculations. The following procedures were employed to generate storm unit hyetographs:

a) Draw a random number between 0 and 24 from a uniform distribution. The number drawn at this point represents the beginning of a storm.
b) Draw a random number from a two-parameter gamma distribution (the gamma parameters should be estimated from observed hourly rainfall characteristics in the area). This number represents the duration of the storm [h] whose beginning was selected under step (a).
c) Add random numbers drawn in steps (a) and (b). If the sum is greater than 24, repeat steps (a) through (c). Otherwise, go to step (d). This is done to make sure that the storm duration is still within the 24 h-day mark after being added to the beginning of the storm.
d) Draw a random number from either exponential or gamma distributions based on the user's choice for 'X' number of times, where 'X' is the nearest integer number generated under step (b). Add the generated random numbers. If the sum of the generated numbers is greater than one, multiply each generated random number by the inverse of the sum, which produces a unit hyetograph. That is, the area under the curve representing rainfall intensities over the duration of a storm is unity—unit hyetograph.

After the unit hyetograph is generated, hourly rainfall data for the simulated duration is the product of ordinates in the unit hyetograph and total daily rainfall. To generate random numbers for steps b, c and d, variables' estimates are required. We estimated the parameters from 5-year (1997–2001) hourly rainfall data in the Cedar Creek watershed and 5-year (1999–2003) hourly rainfall data for the Upper Trinity basin (Tables 4 and 5). We used the same parameters in Table 5 to disaggregate daily rainfall records into hourly dataset at the Cedar Creek watershed for years between 1963 and 1987. Our hourly rainfall data suggested that storm intensities

Table 5 Statistical parameters used to disaggregate daily rainfall data into hourly data and their estimates

Storm property	Distribution	Parameters	
		Cedar Creek[a]	Upper Trinity[b]
Storm duration	Two parameter gamma	Shape = 0.736053 Scale = 0.278795	Shape = 0.747243 Scale = 0.487645
Storm intensity	Exponential	Shape = 1.4	Shape = 1.3

'Shape' and 'scale' are the shape and scale parameters of respective distributions, respectively

[a]Data, hourly rainfall from 1997–2001

[b]Data, hourly rainfall from 1999–2003

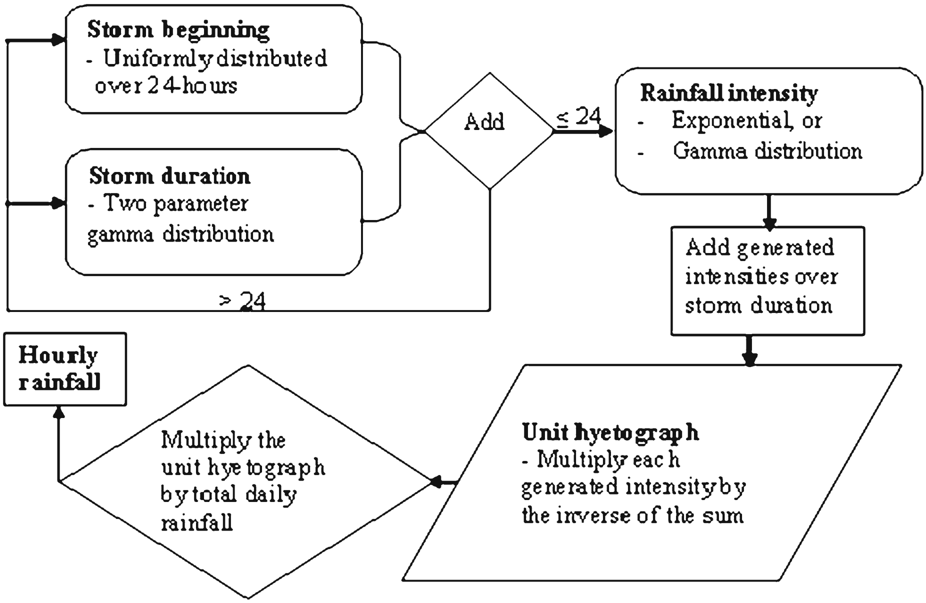

Fig. 3 A stochastic daily rainfall disaggregation scheme flowchart

follow exponential distribution (Debele 2005). Steps followed for random number generation and unit hyetograph creation are also represented in a flowchart (Fig. 3).

2.1.2 Multivariate Rainfall Disaggregation

A multivariate scheme accounts for both spatial and temporal rainfall disaggregation approaches. It combines the stochastic temporal disaggregation scheme employed in the univariate disaggregation method with the spatial correlation that exists between rainfall characteristics at different gauge stations. The number of gauge stations with hourly and daily rainfall data at the Cedar Creek and Upper Trinity basins is shown in Table 4. To examine the spatial relationships that exist between rainfall distributions at different gauge stations, we first aggregated the hourly rainfall data at gauge stations with hourly rainfall records (two stations at Cedar Creek and four stations at Upper Trinity) into daily rainfall datasets. We then calculated lag-zero cross-correlations between daily rainfall data at all gauge stations (two *Vs* nine in Cedar Creek and four stations *Vs* 14 in Upper Trinity) in both watersheds. Daily rainfall data at each of the nine daily stations in the Cedar Creek watershed were cross-correlated at lag-zero with the daily rainfall data at the two hourly gauge stations. Each of the daily stations (gauges 1 through 9) was assigned either hourly gauge 1 or gauge 2 as a pilot station based on the values of the lag-zero cross-correlations. We used similar approaches for the Upper Trinity basin where daily rainfall data at each of the 14 daily stations were cross-correlated at lag-zero with daily rainfall data at all four hourly stations. Each daily station (gauges 1 through 14) was assigned to one of four hourly gauges (gauges 1 through 4) as its pilot station based on the values of the lag-zero cross-correlation. We then disaggregated daily rainfall amounts at each daily gauge station (nine stations at Cedar Creek and 14 stations at Upper

Trinity) into hourly values based on the hourly rainfall characteristics at the assigned pilot stations, but conditioned on its total daily rainfall data (Koutsoyiannis et al. 2001; Debele 2005; Debele et al. 2007). At times when there were data collected at daily stations but not at the assigned pilot stations (which was very rare), we used a univariate approach to disaggregate daily rainfall data into hourly dataset.

2.2 Modification of the ESWAT Model

The ESWAT model has been further modified to incorporate hourly potential evapotranspiration (PET) and overland flow routing modules. The modified ESWAT version calculates PET based on hourly weather data following two approaches: the Priestley–Taylor and Penman–Monteith equations (see FAO paper 56: Allen et al. 1998, for more information). Hourly weather data needed in the computation of hourly PET, for example, solar radiation, air temperature, wind speed and relative humidity were distributed from daily corresponding data of solar radiation, maximum and minimum temperature, wind speed and relative humidity data, respectively, based on a combination of sinusoidal and random functions (Waichler and Wigmosta 2003; Debele 2005; Debele et al. 2007). Although we incorporated both methods of calculating hourly ET in the modified ESWAT model, we used the Penman–Monteith equations for this study due to its superior application in the area (Debele 2005; Debele et al. 2007).

In addition, hourly overland flow routing was also incorporated into the new ESWAT version by subjecting all runoff variables to undergo a time convolution before reaching the main channel. We used the Nash cascade algorithm (Nash 1958; Szilagyi 2003) assuming four virtual reservoirs to transform the runoff variables. We optimized for the number of virtual reservoirs that produced better runoff results, and that number for the Upper Trinity basin was four. The Nash Cascade algorithm (Nash 1958) is represented by the following equations:

$$Q_t = \mathrm{RF}_{\mathrm{EXCESS}} {}^{*} U_t \tag{1}$$

Where Q_t is the rate of outflow [m^3/s], $\mathrm{RF}_{\mathrm{EXCESS}}$ is rainfall excess [m^3/s], and U_t is the instantaneous unit hydrograph, given by:

$$U_t = \frac{1}{K\Gamma(N)} \left(\frac{t}{K}\right)^{N-1} e^{-t/K} \tag{2}$$

Where K is the retention coefficient, N is the number of reservoirs in the series, and t is time [h]. The instantaneous unit hydrograph in Eq. 2 is assumed to follow a gamma distribution—$\Gamma(N)$. In the modified ESWAT model, we also used the RWQM (as introduced by Shanahan et al. 2001 and Van Griensven 2002) to simulate the in-stream water quality processes.

2.3 Goodness-of-fit Statistics

Various methods of model efficiency testing are available. We used the most commonly applied goodness-of-fit statistics in hydrology: the percent bias, Spearman correlation coefficient and the Nash–Sutcliffe model efficiency coefficient (Nash and Sutcliffe 1970). They are given by:

a) Percent bias (bias):

$$bias = \frac{\sum x - \sum y}{\sum y} * 100 \tag{3}$$

b) Spearman correlation coefficient (r)

$$r = \frac{n \sum xy - \sum x \sum y}{\sqrt{\left[n \sum x^2 - \left(\sum x\right)^2\right]\left[n \sum y^2 - \left(\sum y\right)^2\right]}} \tag{4}$$

c) Nash–Sutcliffe coefficient (NS)

$$\mathrm{NS} = 1 - \frac{\sum (x - y)^2}{\sum (y - \bar{y})^2} \tag{5}$$

Where x and y are simulated and measured observations, respectively; n is the number of paired observations and $\overline{y}$ is the mean of measured observations, given by:

$$\bar{y} = \frac{\sum y}{n} \tag{6}$$

The value of r varies between -1 and +1 (the closer the values to +1, the better the model predictions are). Whereas, for the NS the value can vary between $-\infty$ and +1 (the closer the values to +1, the better the model performances are). In addition, we also used most commonly employed statistics for regression analyses and significance testing of the regression parameters (R^2, standard error of estimate—SEE, T-test and probability level) for performance evaluations of the original and modified ESWAT models, and water quality simulations.

3 Results and Discussions

3.1 Rainfall Disaggregation Methods

The overall analyses of performances by each rainfall disaggregation scheme are depicted in Fig. 4 and Table 6. Figure 4 shows the results of sample storm events achieved by various daily rainfall disaggregation schemes at two gauge stations (Stn3 and Stn4). Both the univariate and multivariate approaches reproduced observed peaks very well except that the univariate approach estimated hourly rainfall distribution whose peak is 10 h in front of the actual peak. The multivariate rainfall disaggregation approach produced observed hourly rainfall distribution (including time to peak) relatively well. Similar results were obtained with many more storm events (Table 6). The statistical values computed under each column depict how close the different daily rainfall disaggregation schemes reproduced the actual rainfall distribution. Higher correlation (0.785) and model efficiency coefficients (0.803) under multivariate approach, compared with univariate (r = 0.204, NS = 0.198) and uniform (r = 0.237, NS = 0.212) methods of daily rainfall disaggregation emphasizes

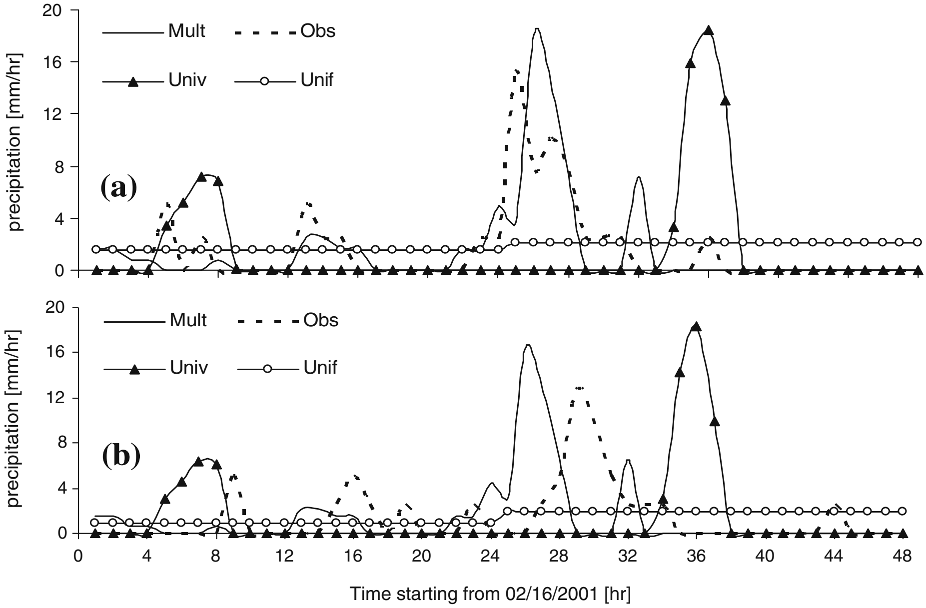

Fig. 4 Observed *Vs* generated hourly rainfall data at two weather stations in the Upper Trinity basin: Stn3 (**a**) and stn4 (**b**). *Obs*, *Unif*, *Univ*, and *Mult* are the observed, and generated hourly precipitation data following uniform, univariate and multivariate disaggregation schemes, respectively

the importance of not just the stochasticity of diurnal rainfall distributions, but also the spatial correlations that exist among neighboring rain gauge stations.

Comparisons of hourly observed versus simulated runoff data are shown in Fig. 5 and Table 7. Hydrographs in Fig. 5 are simulated using the modified ESWAT model based on the rainfall distributions shown in Fig. 4. Runoff hydrographs estimated using rainfall data disaggregated based on uniform distribution, univariate and multivariate disaggregation methods are depicted in Fig. 5. Also, Fig. 5 shows the runoff hydrographs computed from observed rainfall and measured runoff time series data. None of the daily rainfall disaggregation schemes, including observed rainfall data, exactly reproduced the observed runoff hydrograph. However, the multivariate rainfall disaggregation scheme reproduced the runoff hydrograph simulated using observed rainfall data very well. The two curves in Fig. 5 (Mult and Obs_RF)

Table 6 Results of the statistical analyses preformed between observed and simulated hourly rainfall data produced using different rainfall disaggregation techniques; data from the Upper Trinity basin, 1999–2003

Description	Rainfall data disaggregated following		
	Uniform	Univariate	Multivariate
Correlation coefficient	0.237	0.204	0.785
Nash–Sutcliffe coefficient	0.212	0.198	0.803
Total basin-wide rainfall over 5 years (mm)	3381.5	3381.5	3381.5

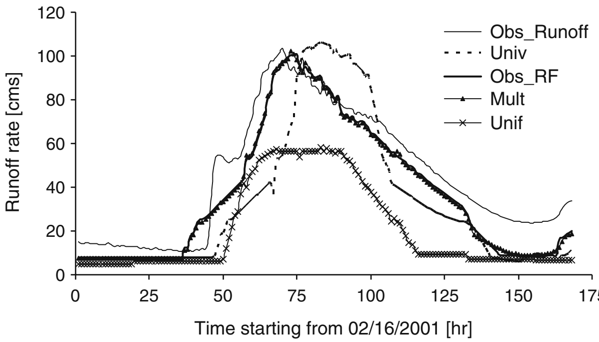

Fig. 5 Observed *Vs* simulated hourly runoff distributions in the Upper Trinity watershed using the modified ESWAT model. *Mult*, *Univ*, and *Unif* are the simulated hourly runoff distributions using hourly rainfall data that were disaggregated from daily data using multivariate, univariate, and uniform rainfall disaggregation techniques, respectively; *Obs_Runoff* and *Obs_RF* are the measured and simulated (using observed hourly rainfall data) hourly runoff distributions, respectively

overlaid for most of the runoff durations. On the other hand, although the peak runoff was reproduced using the univariate disaggregation scheme, the center of the hydrograph peak was shifted by about 18 h in front of the actual observed peak (Fig. 5). The implications of the above assessments are that the multivariate rainfall disaggregation scheme not only reproduced observed peak runoff rate, but also the time to peak, which is one of the requirements in flood control studies. On the other hand, the univariate approach did not reproduce the time to peak, which makes it not a method of choice for flood management in watersheds with a time of concentration of less than a day. However, if time of peak is not the main concern, or if there are no hourly rainfall data in the nearby stations, the univariate approach can be used just as effectively.

Also, Fig. 5 and Table 7 show that the uniform distribution of daily rainfall over 24 h significantly undermined the amount of runoff produced. The uniform rainfall distribution method resulted in a bias of about 9.8% in total runoff over

Table 7 Results of the statistical analyses achieved between observed and simulated runoff data using the modified ESWAT model; data from the Upper Trinity basin, 1999–2003

Description	Observed runoff[a]	Runoff estimated using hourly rainfall data (a) observed, and (b) disaggregated from daily rainfall data using some schemes			
		Observed rainfall	Uniform	Univariate	Multivariate
Correlation coefficient	1.00	0.713	0.187	0.154	0.651
Nash–Sutcliffe coefficient	1.00	0.684	0.142	0.114	0.635
Total runoff over 5 years (10^6 m^3)	1,064	1,063.2	960	1,050	1,062.3
Percent bias	0.00	−0.08	−9.8	−1.32	−0.16

[a]Statistical values under this column were obtained by comparing against itself (Observed *Vs* Observed)

the 5 year period, while the univariate and multivariate disaggregation schemes reproduced observed runoff quantity reasonably well (bias <2%). The large bias using uniform rainfall distribution over 24 h of the day may be attributed to the spread of daily rainfall data over longer durations as opposed to high intensity and short-lived rainfall storm characteristics in the area (US SCS 1986). Longer duration and low intensity storms produce less runoff in areas characterized by Hortonian-type infiltration, compared to high intensity and short-lived storms.

The multivariate rainfall disaggregation scheme also produced runoff with a good correlation coefficient (r = 0.651) and Nash–Sutcliffe model efficiency coefficient (NS = 0.635), compared with observed time series runoff data (Table 7). The low correlation coefficient under the univariate disaggregation scheme (r = 0.154), despite good agreements in the total runoff produced with observed runoff (bias = 1.32%), could be attributed to the time difference between observed and simulated runoff time series data (Fig. 5). This could be because the appropriate univariate disaggregation model would only generate a synthetic hourly series, fully consistent with the known daily series and, simultaneously, statistically consistent with the actual hourly rainfall series. Yet, rainfall series obtained by such a disaggregation method could not coincide with the actual one, but would be a likely realization (Koutsoyiannis 2001; Debele 2005; Debele et al. 2007). In addition, the sub-watershed (section above USGS08044500 gage station) has a relatively shorter time of concentration owing to the watershed characteristics. Thus, there would be a fast response from the watershed at the outlet due to changes in rainfall distributions, which eventually leads to the discrepancy in runoff time series. Nonetheless, using the multivariate rainfall disaggregation approach, one could utilize the available hourly rainfall information at the neighboring stations to generate a spatially and temporally consistent hourly rainfall series at the raingage of interest (Koutsoyiannis et al. 2001; Debele et al. 2007).

3.2 The Modified ESWAT Model

Since the multivariate rainfall disaggregation scheme had better performances in our study areas (Debele et al. 2007; Table 6; Fig. 4), we used similar and more simplified approach to disaggregate daily rainfall data into hourly data for use in the ESWAT model assessments. Comparisons between the original and modified ESWAT models are depicted in Fig. 6, and Tables 8 and 9. The addition of hourly PET and overland flow routing modules has greatly improved hourly predictions in the modified ESWAT model. In Fig. 6, the modified version shows temporal variability in the runoff hydrograph similar to what was observed on the ground while the original ESWAT model produced a uniformly distributed runoff hydrograph over the flow duration. Table 8 depicts the global analyses of comparisons between original and modified ESWAT versions at the Upper Trinity watershed. The correlation coefficients of r = 0.643 versus r = 0.713, the Nash–Sutcliffe model efficiency coefficients of NS = 0.589 versus NS = 0.684 and the percent biases of bias = −0.45 versus bias = −0.16 between runoff data simulated using the original and modified ESWAT versions, respectively, clearly indicate that the modified ESWAT version performed better. One justification for the improvements gained by applying the modified ESWAT version can be offered by looking at how PET is computed in both cases. In the original ESWAT model, PET is calculated from daily average

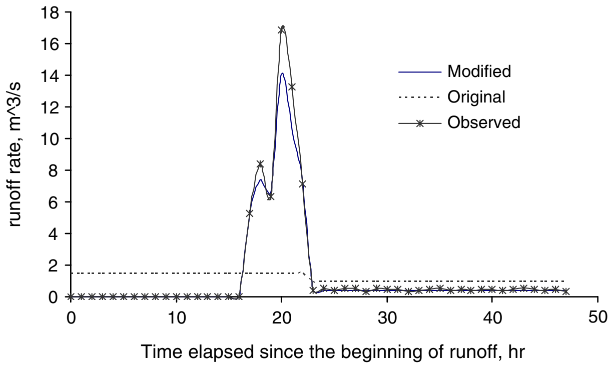

Fig. 6 Hourly runoff simulations using the original and modified ESWAT versions starting from 08/06/2002 (data from Upper Trinity watershed). 'Observed' stands for time series data of hourly measured runoff

temperature, which itself is estimated by halving the summation of daily maximum and minimum temperatures. Yet, average daily temperature computed in this fashion slightly under-predicted the true average daily temperature in the study area (Debele 2005; Debele et al. 2007). On the contrary, in the modified ESWAT version PET is calculated based on hourly distributions of climate–soils–vegetation feedback, which is a closer representation of reality.

Another justification for the improvements gained by applying the modified ESWAT version could also be provided by comparing how the two model versions account for overland flow from each HRU. In the earlier ESWAT version, overland flow from each HRU is directly added to the main channel by assuming that all HRUs are directly connected to the main channel of the sub-basin, which may or may not be true in reality since some HRUs are connected to the main channel through other HRUs and therefore need some kind of overland flow routing to better represent the physical processes of water movement. Whereas, in the revised version of the ESWAT model, to compensate for the limitation due to such assumption in the original SWAT framework, we subjected runoff variables from each HRU to go through a series of reservoir cascades (adopting a Nash cascade algorithm—Nash 1958) to smoothen runoff hydrograph from subbasins. This approach ensures better representation of reality, especially in watersheds that are sub-divided into larger

Table 8 Results of the statistical analyses comparing observed and simulated runoff data using different ESWAT versions; data from Upper Trinity watershed, 1999–2003

Statistical description	Observed runoff[a]	Original ESWAT	Modified ESWAT
Correlation coefficient	1.00	0.643	0.651
Nash–Sutcliffe coefficient	1.00	0.589	0.635
Total runoff over 5-year period (10^6 m^3)	1064	1059.2	1062.3
Percent bias	0.00	−0.45	−0.16

[a]Statistical values under this column were obtained by comparing against itself (Observed *Vs* Observed)

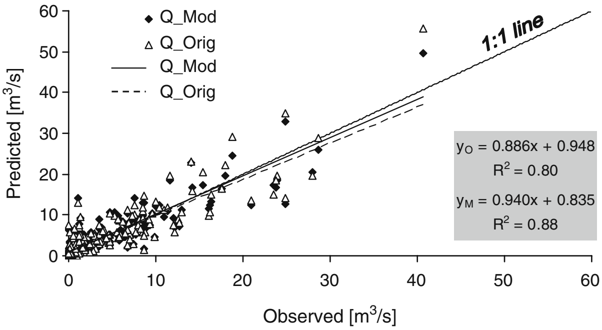

Fig. 7 Monthly distributions of measured (1:1 line), and simulated using the modified ESWAT model (*Q_Mod*) and original ESWAT model (*Q_Orig*) runoff data at USGS2800 gage station, Cedar Creek watershed (data from 1963–1987). Y_O and Y_M are regression equations fitted from runoff predictions by the original and modified ESWAT models against the measured runoff values (x), respectively

subbasins which have complex land use and soils distributions (i.e., cases where there are higher number of HRUs that may not be directly connected to the subbasin's main channel).

Figure 7 depicts the scatter plots of monthly runoff simulations aggregated from hourly runs for the period of 25 years (1963–1987). The appropriateness of the modified model can also be justified on such grounds that the monthly variations in runoff hydrograph were more closely reproduced using the modified ESWAT model, compared with the original one (Fig. 7; Table 9). The modified ESWAT model had a closer regression line to the 1:1 line, compared with the original ESWAT version. Table 9 depicts the overall statistics computed as a result of using the modified and original ESWAT models. The higher model efficiency coefficient (determined by the Nash–Sutcliffe coefficient) and lower percent bias estimated by using the modified ESWAT model, compared with the original ESWAT version over longer simulation period (25 years) reaffirms that the modification made to the ESWAT model actually improved the model's overall hydrological performances.

Table 9 Results of the statistical analyses comparing monthly runoff distributions (accumulated from hourly runs) computed using the original and modified ESWAT models; data from the Cedar Creek watershed, 1963–1987

Statistical description	Observed[b]	Original ESWAT	Modified ESWAT
R^{2a}	1.00	0.80	0.88
Nash–Sutcliffe coefficient	1.00	0.76	0.79
Total runoff over 25 year period (10^{18} m^3)	1.327	1.566	1.453
Percent bias	0.00	+18.0	+9.5

[a] R^2 is the square of the correlation coefficient, r

[b] Statistical values under this column were obtained by comparing against itself (Observed *Vs* Observed)

3.3 Water Quality Analyses

One of the most difficult and yet very important components in water quality modeling is the availability of detailed temporal and spatial recorded dataset against which model predictions could be examined. Water quality data are mostly collected through grab samples, and rarely on continuous temporal scales owing to the expensive running costs involved. Even if temporally continuous water quality measurements are available at few gauging stations, those may not be sufficient to calibrate a water quality model in a complex watershed where most of its pollutants emanate from diffuse sources—that requires water quality data at detailed spatial scales as well. Luckily, if the physics of water movement is well-captured, and a physically based upland watershed and in-stream water quality model is used, there is a high likelihood of sufficiently estimating pollutant loads at some predefined gauge stations in a watershed. A combination of good modeling practice and use of available resources is what should be applied to facilitate water resources management in complex watersheds. With this code of practice, we simulated the water quality variables at the Cedar Creek watershed despite insufficient water quality data at required temporal and spatial scales to calibrate our models.

Figures 8 and 9 show simulated versus measured daily scatter plots of nutrients and sediments (total suspended solids) for the period of 5 years (1997–2001) in the Cedar Creek watershed using the modified ESWAT model. Regression equations and R^2 values of the regressions between measured and predicted water quality variables are also depicted in Figs. 8 and 9. Comparisons of observed versus simulated daily

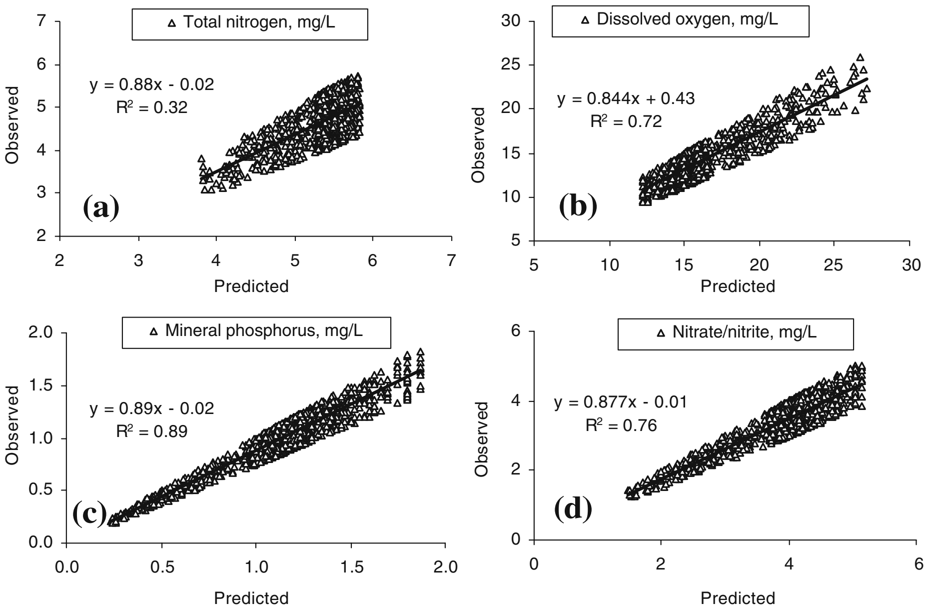

Fig. 8 Measured *Vs* calibrated daily nutrients concentrations at USGS2800 gage station. **a**, **b**, **c** and **d** Represent measured and calibrated graphs for total suspended sediment, organic nitrogen, organic and total phosphorus concentrations, respectively; data from Cedar Creek watershed, 1997–2001

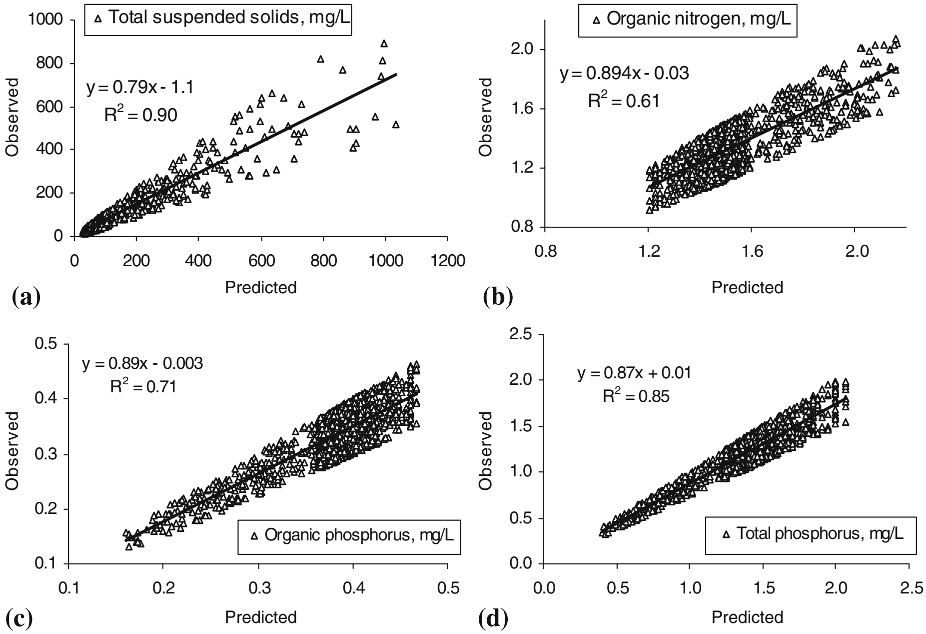

Fig. 9 Measured *Vs* calibrated daily sediments and nutrients concentrations at USGS2800 gage station. **a**, **b**, **c** and **d** Represent measured and calibrated graphs for total suspended solids, organic nitrogen, organic phosphorus and total phosphorus concentrations, respectively; data from Cedar Creek watershed, 1997–2001

sediments (TSS), organic nitrogen and phosphorus, and total phosphorus are shown in Fig. 8a–d, respectively. Similarly, comparisons of observed versus simulated daily total nitrogen, dissolved oxygen, mineral phosphorus and nitrate/nitrite concentrations are described in Fig. 9a–d, respectively. Table 10 shows the percent bias between observed and simulated water quality loads; R^2 and standard error of estimate of the regression lines; and the SEE, T-test and probability of significance of the regression lines' slopes and intercepts determined by measured and predicted water quality variables. The slopes of all the regression lines are significantly different from zero ($P < 0.0001$). In addition, the table shows that all the intercepts of the regression lines between measured and predicted water quality datasets are not significantly different from zero ($P > 0.05$) at 5% significance level. These values confirm the statistically non-significant difference between measured (1:1 line) and model predicted water quality variables.

Mineral phosphorus (Fig. 8c and Table 10) was the most well-reproduced of all water quality variables covered (bias = 8.9%; $R^2 = 0.89$). A bias of less than ±20% and R^2 values ≥ 0.60 with the exception of total nitrogen ($R^2 = 0.32$)) were achieved upon calibration in all water quality variables examined (Table 10). Statistical values of these magnitudes are as good as or better than those regularly reported in most water quality studies (Robertson and Roerish 1999; Sincock et al. 2003; Robinson et al. 2004). Sincock et al. (2003) reported R^2 values ranging from 0.23 to 0.64 between observed and simulated water quality parameters (NO3, BOD and DO).

Table 10 Bias, regression analyses and the corresponding statistical significance of regression parameters for datasets described in Figs. 8 and 9; data from the Cedar Creek watershed, 1997–2001

Water quality	R^2 bias[a]	Regression SEE	Regression parameters	Values	SEE	*T-stat*	*P-value*
TSS	0.901	17.803	Intercept	−1.117	0.630	−1.564	0.120
	18.0%		Slope	0.793	0.008	87.963	< 0.0001
TP	0.854	0.134	Intercept	0.014	0.016	−0.237	0.812
	19.0%		Slope	0.866	0.012	70.990	< 0.0001
MINP	0.887	0.105	Intercept	0.002	0.011	0.199	0.842
	8.9%		Slope	0.893	0.009	90.316	< 0.0001
ORGP	0.712	0.036	Intercept	−0.003	0.007	−1.418	0.156
	17.5%		Slope	0.887	0.017	49.257	< 0.0001
TN	0.321	0.508	Intercept	−0.023	0.213	−0.929	0.353
	12.5%		Slope	0.882	0.040	21.974	< 0.0001
NO_2/NO_3	0.760	0.374	Intercept	−0.012	0.060	0.470	0.639
	−16.8%		Slope	0.877	0.015	54.578	< 0.0001
ORGN	0.608	0.140	Intercept	−0.027	0.033	−0.220	0.826
	14.7%		Slope	0.894	0.021	39.274	< 0.0001
DO	0.720	1.203	Intercept	0.432	0.261	0.133	0.894
	15.4%		Slope	0.844	0.016	51.177	< 0.0001

[a]The second lines in this column represent percent bias between observed and simulated water quality loads using the modified ESWAT model; SEE, T-test and P-value are the standard error of estimate, student T-test values, and the probability, respectively

Given the difficulty of obtaining generally expensive water quality data at required temporal and spatial scales, and accompanying measurement errors, the error of this magnitude (±20%) is acceptable. The most encouraging aspect of this study's result is that despite the dearth of detailed measured water quality data, the model gave good calibration results. It is also very encouraging to observe how well the overall maxima and most local maxima have been reasonably accurately predicted for almost all analyzed water quality parameters (Figs. 8 and 9). Few exceptions do, however, exist where some spikes were missed by the model (Figs. 8a, b, 9a, b). In the case of Fig. 8a, predicted versus measured daily sediments concentrations did not fall on the straight line at higher sediment concentration levels—daily sediment concentrations were slightly under-predicted. Similarly, measured versus simulated daily organic nitrogen (Fig. 8b), total nitrogen (Fig. 9a) and dissolved oxygen (Fig. 9b) concentrations' scatter plots were all over the places (i.e., not exactly following the straight line).

One possible explanation for the discrepancies between measured (itself estimated by LOADEST2 program) and simulated sediments and nutrients concentrations could be due to the error propagation effect. Errors introduced when generating daily water quality data by the LOADEST2 program may have adversely affected the correlation between daily water quality data predicted by the two models (one by ESWAT model and the other generated by the LOADEST2 model). We want to call the attention of our readers that in this exercise, we did not have measured daily water quality data, but instead we had water quality data measured at weekly and sometimes at bi-weekly intervals. However, we used a robust model

(LOADEST2—Runkel et al. 2004) to generate daily water quality data from observed daily runoff data after having the model trained with historical water quantity and quality relationships at the same gauge station (please see Runkel et al. 2004; White and Chaubey 2005, among others, for further reading on LOADEST2 model). Similarly, in the ESWAT model, ET was computed based on model generated hourly solar radiation, temperature and wind speed data (Debele et al. 2007). The errors introduced while estimating these datasets might have also propagated to estimation of hourly ET by the ESWAT model, which in turn may also spread to flow estimation error by the ESWAT model, and hence water quality evaluation.

Models serve multiple objectives, of which one is guiding decision making. This is one of those models that can be used by water resources managers and decision makers to help guide what additional data should be collected, what should be done about the problems identified, and which problems should be solved first if prioritization is required. In addition, given the model's capacity to simulate water quantity and quality processes at detailed temporal and spatial scales, a water resources planner can use this and similar models to identify hotspots within complex river basins and prioritize implementation of appropriate adaptations accordingly—i.e., implementation of integrated water resources management at river basin scale.

4 Conclusions

We have conducted a thorough study of improving the ESWAT model through further incorporation of hourly ET and overland flow routing modules. The results from both hydrological and water quality simulations indicate that the addition of hourly ET and overland flow routing modules improved the outcome. In addition, we also developed a simple methodology to disaggregate daily rainfall data into hourly data, and carried out comparisons of daily rainfall disaggregation methods following uniform, univariate and multivariate approaches against measured hourly rainfall data. The results indicate that the multivariate disaggregation method reproduced observed rainfall data very well, compared with other methods. Consequently, we have also compared measured hourly runoff hydrographs with those obtained by running the modified ESWAT model using measured hourly rainfall data and those disaggregated hourly rainfall data (using uniform, univariate and multivariate disaggregation schemes). Again, the results indicate that the multivariate rainfall disaggregation method reproduced runoff hydrographs obtained using observed rainfall data very well, compared with other methods.

Despite the absence of enough measured water quality data at required temporal scales (hourly or daily), we were able to compare model predictions for commonly collected diffuse source water quality variables. This study shows some very interesting and encouraging results in water quality modeling although little measured water quality data is available. This should not mean that we do not need enough data to test such water quality models, but that a model of this sort could be used as a management tool both to identify which water quality data should be collected, to prioritize implementation of watershed managements, and to further alleviate the problems identified hitherto.

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