Evaluating Urban Pollutant Buildup/Wash-Off Models Using a Madison, Wisconsin Catchment

Stephen B. Shaw1; Jery R. Stedinger2; and M. Todd Walter3

Abstract: Buildup/wash-off (BUWO) models are widely used to estimate pollutant export from urban and suburban watersheds. Here, we propose that the mass of washed-off particulate during a storm event is insensitive to the time between storm events (the traditional predictor of particulate accumulation in BUWO models). Our analysis employed USGS data of total suspended solids and discharge data for nonsnow events in a 9.4-km² suburban catchment in Madison, Wis. Kinetic energy of rainfall was calculated using National Weather Service NEXRAD radar reflectivity. A regression analysis found that storm event runoff volume and rainfall kinetic energy explained 81% of the variability in event particulate load; volume alone explained 69% of the variability in event loads. Time between storm events was not significant. Additionally, we simulated storm event particulate loads using a BUWO model and a model assuming a constant mass available for wash-off. Both models produced very similar predictions over a range of parameterizations, suggesting that buildup models could perhaps be simplified under many circumstances.

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Author keywords: Nonpoint source pollution; Urban hydrology; Buildup/wash-off models; NEXRAD Level II Data.

Introduction

Runoff from urban and suburban areas often transports pollutants including nutrients, heavy metals, and pathogens to nearby water bodies (U.S. EPA 1983). A large fraction of these pollutants are associated with particulate matter (Sansalone and Buchberger 1997; Vaze and Chiew 2004). A clear understanding of sources and processes affecting particulate transport can aid in developing strategies to reduce particulate export to surface waters (Vaze and Chiew 2004).

Particulate pollutant loss from urban and suburban catchments representing a mix of pervious and impervious surfaces has been calculated using simple event mean concentration (EMC) models and by using more sophisticated buildup/wash-off (BUWO) models. An EMC model assumes a single flow weighted concentration can be used across an entire storm event (Charbeneau and Barrett 1998). However, because the EMC may change between storms (U.S. EPA 1983), load predictions for unmonitored events can be inaccurate. To try to account for EMC variations between storms, urban BUWO models have been formulated to predict particulate loads as functions of the particle mass that has built up on the surface between storm events (see, e.g., Chen and Adams 2007). BUWO models are a standard feature of widely used water quality models such as the storm-water management model (SWMM) (Huber and Dickinson 1988). However, SWMM can include many other processes (e.g., Tsihrintzis and Hamid 1998), and the presumed BUWO processes are seldom (if ever) assessed against internal, subcatchment scale observations.

The buildup assumption is frequently justified by the work of Sartor and Boyd (1972). However, Sutherland and Jelen (2003) noted that a central figure justifying buildup in the Sartor and Boyd report (Sartor and Boyd 1972, p. 208) shows mass accumulation functions being forced to pass through the origin at zero days antecedent buildup, suggesting that particulate mass always drops to zero and exaggerating the degree to which particulate mass changes in interstorm periods. Sutherland and Jelen (2003) independently conclude that residual particulates are most likely always present on urban surfaces. Furthermore, in other parts of the Sartor and Boyd report, even Sartor and Boyd themselves presented a more complete picture of buildup. For example, a qualitative graphic of buildup shows a nonzero pollutant loading at time zero after a storm (Sartor and Boyd 1972, Fig. 4, p. 34).

Other work has also questioned whether accounting for buildup can actually explain variations in washed-off particulate load. Charbeneau and Barrett (1998) related antecedent dry days (a typical proxy for the amount of buildup) to particulate load for eight sites in Austin, Tex., and found no trend. In evaluating wash-off models against a data set from Australia, Vaze and Chiew (2003) assumed all wash-off events started with the same available surface mass, effectively assuming surfaces have a relatively constant available mass. From other works in Australia, Egodawatta et al. (2007) measured total particulate mass available on urban surfaces before storm events and found similar wash-off quantities even with different amounts of particulate initially available. In adding a factor to account for antecedent dry

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days to a linear, multifactor wash-off model, Soonthornnonda and Christensen (2008) increased the $R^2$ between observed and estimated total suspended solid (TSS) loads from 0.23 to 0.38, based on 411 storm events in urban watersheds near Milwaukee. While this is a moderate increase in $R^2$, the overall explanatory power of the model remained small. In a study of street sewer effectiveness in small, Madison, Wis. watersheds (adjacent to the watershed assessed in this paper), no definitive link could be made between mass of material removed by sweeping and particulate loads in storm sewers (Selbig and Bannerman 2007).

We have two primary objectives for this paper. First, given that buildup has frequently been employed to explain interstorm variability in particulate load, we explore alternate factors to describe this variability, including the kinetic energy of rainfall impact. Kinetic energy has long been included in soil erosion models (see Wischmeier and Smith 1958). While early researchers (Sartor and Boyd 1972) recognized the importance of water impact energy on the ability to move particulates, neither rain drop nor overland flow energy is typically included in lumped models of wash-off. Only recently have researchers again started to recognize that rain drop kinetic energy may be useful in predicting particle wash-off in urban areas (Vaze and Chiew 2003; Egodawatta et al. 2007; Brodie and Rosewell 2007). Because rainfall kinetic energy is a nonlinear function of spatially and temporally variable rainfall intensity, standard aggregate measures such as discharge, total runoff volume, and average intensity may not reveal differences in kinetic energy. We make use of National Weather Service NEXRAD radar data to assess high resolution rainfall patterns (approximately 1-km$^2$ grid size, 5-min time interval). Investigators have used spatially variable rainfall in hydrologic models (Ogden et al. 2000; Smith et al. 2005; Kalin and Hantush 2006) and spatially variable erosion models with uniform rainfall (Jain et al. 2005), but the two have not generally been combined. Cruse et al. (2006) combined NEXRAD radar with the WEPP erosion model to predict daily erosion across Iowa, but the model was not compared to actual measurements of soil loss in streams.

Rainfall kinetic energy’s possible explanatory value can be seen qualitatively by considering two events that are similar hydraulically (they have the same peak flow) but differing instantaneous TSS concentration at the peak discharge. The event in Fig. 1(a) has an instantaneous TSS concentration of 235 mg L$^{-1}$ while that in Fig. 1(b) has a concentration of 430 mg L$^{-1}$. Radar reflectivity maps for each event indicate different rainfall patterns; in this case, a narrow, high-intensity front in Fig. 1(b) and a more expansive, slower moving storm in Fig. 1(a). The cumulative kinetic energy during the 30 min before the peak discharge is larger for the high-intensity front shown in Fig. 1(b) (4.07 $\times$ 10$^8$ MJ over 30 min) compared to the more diffuse storm event in Fig. 1(a) (9.16 $\times$ 10$^7$ MJ over 30 min), which potentially explains the difference in TSS concentrations.

Our second objective is to evaluate if the extra complexity of the BUWO model is even necessary for accurately predicting wash-off. We suggest that in many cases where available particulate for wash-off does not become depleted (i.e., a relatively constant supply of particulate is available), the particulate load estimated by a buildup model is predominantly determined by the event runoff volume. As long as the model can reproduce runoff volume, the event load will also be reasonable. A simulation study tests whether, for common parameter values, the BUWO model produces similar wash-off estimates as a model that uses a constant mass of particulate available for wash-off.

This paper is organized as follows. The next section introduces background on BUWO models. “Methods” discusses the methods of data collection and compilation. “Explaining Interstorm Variability in Particulate Loads” evaluates kinetic energy and other variables in regression models for explaining interstorm variability in particulate load. “Evaluation of BUWO Models” considers conditions under which BUWO models behave like a model with constant available mass. The two final sections provide discussion and conclusions.

**Model Background**

There is no standard formulation for BUWO models. However, variations among formulations are relatively minor and the conceptual basis remains the same. The basic model can be written

$$M_{t+\Delta t} = M_t + \left\{ k \cdot \left( 1 - \frac{M_t}{m_0} \right) - \alpha \cdot M_t \cdot q_t \right\} \Delta t$$

where $M_t$(kg)=available mass at time $t$; $k$=buildup coefficient (kg time$^{-1}$); $m_0$=threshold at which additional mass does not accumulate on the surface (kg); $q_t$=runoff rate (m$^3$ time$^{-1}$); $\alpha$=wash-off rate constant (m$^2$); and $\Delta t$=time increment. The subscript $t$ indicates the quantities are unique to specific time periods. In Eq. (1), particulate buildup (the second term on the right hand side) is assumed to accumulate asymptotically toward a maximum, $m_0$, in the absence of wash-off. Wash-off [the third term on the right hand side of Eq. (1)] is assumed to occur linearly with $q_t$ and $M_t$. To maintain the mass balance, if the time step is large, an additional constraint is added so that mass loss cannot be greater than the amount on the surface at the beginning of a wash-off event.
A simplification of this BUWO model would be a model assuming a constant available mass (CAM) [Eq. (1) would reduce to \( M_{\text{avg}} = M_{\text{avg}} \)]. With constant available mass, loss in each time step \( \text{Loss} = \frac{q_t \cdot \Delta t}{V} \), equivalent to the third term on the right hand side in Eq. (1) can be written

\[
\text{Loss} = \alpha \cdot M_{\text{avg}} \cdot q_t \cdot \Delta t
\]

(2)

where \( M_{\text{avg}} \) = modeled available mass which can be considered as the average \( M_t \), obtained with the BUWO model [Eq. (1)]. Herein, the application of Eq. (2) in a numerical time-step model will be referred to as the CAM model.

When \( \Delta t \) becomes very small, Eq. (1) can be configured as a pair of differential equations. For a period with no rainfall, Eq. (1) becomes

\[
\frac{dM_t}{dt} = k \left( 1 - \frac{M_t}{m_0} \right)
\]

(3a)

Assuming buildup is negligible during storm events, the change in mass during a wash-off event becomes

\[
\frac{dM_t}{dt} = -\alpha M_t \Delta t
\]

(3b)

The solutions of these differential equations are the frequently used exponential buildup and wash-off equations (e.g., Easton et al. 2007; Chen and Adams 2007)

Buildup: \( M_{\text{in}} = M_0 + (m_0 - M_0) \left( 1 - \exp \left( -\frac{k}{m_0} T_{\text{dry}} \right) \right) \)

(4a)

Wash-off: \( \text{Loss}_{\text{in}} = M_{\text{in}} T_{\text{dry}} \left( 1 - \exp(-\alpha V) \right) \)

(4b)

where \( T_{\text{dry}} \) = number of days since a significant discharge event during which mass accumulates and \( V \) (the storm volume) = integration of \( q_t \) over the storm event duration. The Loss is subtracted from \( M_t \), before calculating the buildup during the next time interval of \( T_{\text{dry}} \). The quantity \( k/m_0 \) in Eq. (4a) is often written as a single parameter which we denote as \( k' \). As long as Eq. (1) is evaluated at short time steps, \( \Delta t \), the models represented by Eqs. (1) and (3) are fundamentally the same.

**Methods**

**Site Description**

In our analyses, we make use of TSS concentration data collected by the USGS at a storm drain outlet in Madison, Wis. (Spring Harbor catchment—USGS #5427965). USGS documentation (available at the website for the gauge) notes that stage height is measured using a “water-stage recorder” at a concrete control. Discharge is accurately back-calculated from stage for discharges between 0.1 and 2.8 m³/s⁻¹. TSS samples were collected using an automatic pump that took a point sample (Sampling Method 82398—Code 50), in contrast to taking a vertically integrated sample in space or a composite sample over time.

The Spring Harbor catchment covers 9.4 km² and consists primarily of suburban residential land use. Watershed boundaries were approximated from USGS topographic maps. The soils consist of sandy and silt loams with saturated conductivities greater than 0.75 m day⁻¹ and depths of at least 2 m (USDA NRCS web soil survey: http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx). A network of drainage pipes underlying much of the watershed conveys storm water to the outlet point.

**Data**

To assess the validity of BUWO models, we use a sequence of 19 storm events from May to November 2002. This includes all storm events during that period in which discharge rises above and then drops back below 0.28 m³ s⁻¹, except for an event on August 11, 2002 for which limited suspended solids data was available and was, therefore, not included in this study. We use consecutive storm events to assure a complete history of particulate loss because wash-off from a storm event can be dependent on what remains after the previous events.

Seven of the 19 events lacked the National Weather Service radar data needed to calculate kinetic energy. Therefore, we only use 12 of those 19 storm events to assess the role of kinetic energy in explaining interstorm variability in loads. To these 12 storms, we added two 2001 storms to supplement the 2002 record, for a total of 14. Table 1 summarizes data from the 21 unique storm event used within this paper.

To estimate event loads from our observed 5-min discharge data, given only 5–6 concentration measures per event, we first establish concentration-discharge \((C-q)\) relationships for each storm event with the form of a power law

\[
C_t = \omega q_t^{\eta}
\]

(5)

where \( C_t \) = TSS concentration at a given time and \( \omega \) and \( \eta \) are fitting parameters. The \( C-q \) relationships for each storm event are calibrated by fitting a least-squares regression line to the available log adjusted \( C \) and \( q \) values. As examples, \( C-q \) relationships from the first five storm events of 2002 are shown in Fig. 2. We performed a \( t \)-test to check whether the slope of the regression line was significantly different than zero (slope=0 indicates no relationship) at the 10% level (assuming independent errors in the residuals) and found that 16 out of the 21 \( C-q \) relationships had a statistically significant relationship. The five \( C-q \) relationships without a statistically significant relationship exhibited an upward trending best-fit line but generally had a single outlier that dominated the small number of data points. Of the 21 regressions, all but five had \( R^2 > 0.85 \). The five lower \( R^2 \) values ranged from 0.56 to 0.75.

An event volume \( (V) \) is calculated as

\[
V = \sum_{t=0}^{T_{\text{end}}} q_t \Delta t
\]

(6)

where \( \Delta t \) = time interval between discharge measurements, typically 5 min during rainfall and 15 min in the receding leg of the storm hydrograph. Because discharge is predominantly ephemeral in the Spring Harbor watershed, the start of most events is easily discerned. The event is considered to begin \( (t=0) \) at the rapid rise in the hydrograph after the initiation of rain and continues until the discharge drops to 0.04 m³ s⁻¹ at some time \( T_{\text{end}} \). If another storm event starts before the hydrograph drops to 0.04 m³ s⁻¹, \( T_{\text{end}} \) is set at the time of minimum discharge before the next event peaks.

An event load \( (L) \) is calculated as

\[
L = \sum_{t=0}^{T_{\text{end}}} q_t C_t \Delta t
\]

(7)

where the function for \( C_t \) [see Eq. (5)] is uniquely calibrated for each storm event. \( L \) is reported in metric tons (mt)

For the 14 storm events with available radar data, we compiled time between storms \( (T_{\text{dry}}) \), total storm runoff volume \( (V) \), rainfall depth \( (R_{30}) \), and kinetic energy \( (KE_{30}) \). Table 2 provides a more
extensive explanation of each variate. Note, we use a 30-min interval for rainfall kinetic energy and depth since nearly all events we looked at had only a 30-min span of intense rain. Extending the interval did not greatly change the kinetic energy attributed to each storm event.

Converting from Radar Data to Kinetic Energy

A single rain gauge (Charminy Farms, NWS Coop #471416) provides only hourly rainfall amounts at a single point within the catchment, so rainfall was instead estimated from radar reflectivity data. The radar data provides greater resolution of spatial variations \(1 \text{ km}^2\) and temporal variations in rainfall intensity over the catchment than would be available from the single rain gauge, an important feature given the convective storm events of concern here. Radar reflectivity \(\text{mm}^6 \text{ m}^{-3}\) is measured on a logarithmic scale in dBZ (decibels). When the radar is operating in precipitation mode in contrast to clear air mode, light rain corresponds to approximately 20 dBZ (Rinehart 1991, p. 119). Of the 14 storm peaks analyzed, the maximum observed reflectivity was 60 dBZ.

Radar reflectivity data over the catchment were obtained from the National Weather Service Archive of WSR-88D NEXRAD Radar Data stored on the National Climate Data Center (NCDC) Robotic Mass Storage System accessible at http://www.ncdc.noaa.gov/oa/radar/radardata.html. The closest station to our catchment was Milwaukee (MKMXX). Typically, we obtained Level 2 reflectivity data at 10-min intervals from 40 min before to 10 min after each storm peak for a total of six images for each event analyzed. The raw Level 2 data were converted to a shapefile using the NCDC Java NEXRAD Data Exporter V. 1.3.5; only reflectivity at the lowest cut angle elevation was selected.

### Table 1. Data Summary of the 21 Storm Events Used in the Two Analyses; Radar Data Was Not Available for Events without KE\(_{30}\), as Indicated by the Dashes

<table>
<thead>
<tr>
<th>Date</th>
<th>(L) (mt)</th>
<th>(V) (1,000s (m^3))</th>
<th>(KE_{30}) (MJ)</th>
<th>(q_p) (m^3 \text{ s}^{-1})</th>
<th>(T_{dry}) (days)</th>
<th>(R_{30}) (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>May 1, 2002</td>
<td>1.31</td>
<td>16.1</td>
<td>—</td>
<td>0.91</td>
<td>3</td>
<td>—</td>
</tr>
<tr>
<td>May 9, 2002</td>
<td>1.70</td>
<td>10.3</td>
<td>291</td>
<td>0.40</td>
<td>8</td>
<td>1.7</td>
</tr>
<tr>
<td>May 11, 2002</td>
<td>1.50</td>
<td>10.5</td>
<td>1,050</td>
<td>0.68</td>
<td>2</td>
<td>5.4</td>
</tr>
<tr>
<td>May 25, 2002</td>
<td>1.64</td>
<td>23.8</td>
<td>345</td>
<td>0.93</td>
<td>14</td>
<td>2</td>
</tr>
<tr>
<td>May 28, 2002</td>
<td>15.70</td>
<td>17.3</td>
<td>—</td>
<td>2.66</td>
<td>3</td>
<td>—</td>
</tr>
<tr>
<td>June 3, 2002</td>
<td>12.00</td>
<td>53.3</td>
<td>4,570</td>
<td>4.31</td>
<td>5</td>
<td>17.7</td>
</tr>
<tr>
<td>June 4, 2002</td>
<td>7.01</td>
<td>87.3</td>
<td>—</td>
<td>2.04</td>
<td>1</td>
<td>—</td>
</tr>
<tr>
<td>June 10, 2002</td>
<td>8.15</td>
<td>40.2</td>
<td>9,750</td>
<td>5.16</td>
<td>6</td>
<td>31.8</td>
</tr>
<tr>
<td>June 13, 2002</td>
<td>0.80</td>
<td>4.3</td>
<td>1,520</td>
<td>1.70</td>
<td>3</td>
<td>7.1</td>
</tr>
<tr>
<td>June 26, 2002</td>
<td>2.57</td>
<td>8.4</td>
<td>2,680</td>
<td>1.78</td>
<td>13</td>
<td>10.5</td>
</tr>
<tr>
<td>July 20, 2002</td>
<td>1.50</td>
<td>8.1</td>
<td>4,070</td>
<td>2.72</td>
<td>24</td>
<td>16.0</td>
</tr>
<tr>
<td>July 22, 2002</td>
<td>3.40</td>
<td>28.1</td>
<td>179</td>
<td>2.83</td>
<td>2</td>
<td>1.1</td>
</tr>
<tr>
<td>August 13, 2002</td>
<td>1.20</td>
<td>18.9</td>
<td>—</td>
<td>1.13</td>
<td>2</td>
<td>—</td>
</tr>
<tr>
<td>August 17, 2002</td>
<td>4.60</td>
<td>14.1</td>
<td>4,810</td>
<td>2.44</td>
<td>4</td>
<td>17.4</td>
</tr>
<tr>
<td>August 21, 2002</td>
<td>12.60</td>
<td>24.2</td>
<td>—</td>
<td>3.77</td>
<td>4</td>
<td>—</td>
</tr>
<tr>
<td>September 2, 2002</td>
<td>3.30</td>
<td>38.2</td>
<td>916</td>
<td>3.20</td>
<td>11</td>
<td>4.7</td>
</tr>
<tr>
<td>September 19, 2002</td>
<td>0.29</td>
<td>7.9</td>
<td>—</td>
<td>0.59</td>
<td>17</td>
<td>—</td>
</tr>
<tr>
<td>September 29, 2002</td>
<td>0.57</td>
<td>13.1</td>
<td>—</td>
<td>0.65</td>
<td>9</td>
<td>—</td>
</tr>
<tr>
<td>October 4, 2002</td>
<td>6.28</td>
<td>69.1</td>
<td>2,810</td>
<td>5.16</td>
<td>5</td>
<td>12.1</td>
</tr>
<tr>
<td>July 17, 2001</td>
<td>1.70</td>
<td>6.0</td>
<td>1,350</td>
<td>1.95</td>
<td>29</td>
<td>12.1</td>
</tr>
<tr>
<td>August 1, 2001</td>
<td>6.12</td>
<td>26.1</td>
<td>818</td>
<td>3.80</td>
<td>6</td>
<td>3.8</td>
</tr>
</tbody>
</table>

Note: See Table 2 for a description of the variables.

## Table 2. Summary of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(k)</td>
<td>Buildup coefficient (kg time(^{-1}))</td>
</tr>
<tr>
<td>(KE_{30})</td>
<td>Sum of kinetic energy for 30-min span before storm peak discharge (MJ)</td>
</tr>
<tr>
<td>(L)</td>
<td>Storm event load (mt)</td>
</tr>
<tr>
<td>(M_f)</td>
<td>Mass on surface in wash-off model (kg)</td>
</tr>
<tr>
<td>(m_0)</td>
<td>Threshold at which additional mass will not accumulate in wash-off model (kg)</td>
</tr>
<tr>
<td>(R_{30})</td>
<td>Radar rainfall depth for 30-min span before storm peak (mm)</td>
</tr>
<tr>
<td>(T_{dry})</td>
<td>Time period without runoff prior to storm event (days)</td>
</tr>
<tr>
<td>(V)</td>
<td>Storm event runoff volume (m(^3))</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>Wash-off constant (m(^3))</td>
</tr>
</tbody>
</table>

Fig. 2. Relationships between discharge and TSS concentration for select storm events
Within ArcGIS, this base reflectivity was clipped to the 9.4-km² catchment boundary and converted to a raster grid with 100-m square cells. From this grid, the distribution of reflectivity values at a given time interval was determined. Table 3 provides an example of the observed reflectivity at each time interval for a storm event.

Reflectivity was converted to rainfall intensity (R, mm h⁻¹⁻¹) using a power law reflectivity-rainfall (Z-R) relationship (R =aZᵇ where Z is the reflectivity in mm³/m³). The Z-R relationship can vary among geographic regions and different storm types, although Rinehart (1991) (p. 119) notes the variations are usually minor. We use previously published Z-R relationships for convective storms (Smith et al. 2005), where a=0.017 4 and b=0.71.

To evaluate the reasonability of this Z-R relationship in our catchment, we compared the hourly rainfall measured at the Charminy Farm gauge to area average rainfall determined from radar during the same time interval. Gauge rainfall was missing for several months, so not all events were included in the comparison. As shown in Fig. 3, there are discrepancies between the point gauge and areal average radar data determined using the Z-R relationship reported earlier (if perfectly matched, points would fall along the gray 1:1 line). However, the Z-R relationship has no apparent systematic bias and appears reasonably robust given other uncertainties in the point gauge measurement and radar measurements. There are many sources of inaccuracy in rainfall estimates derived solely from radar reflectivity [Krajewski and Smith (2002) reviewed the possibilities]. Still, the estimates suit the purposes of this paper: to evaluate a possible statistical relation between estimated kinetic energy and the actual observed wash-off in urban areas.

R was converted to kinetic energy (KE) (J) using a power law relationship fitted to the data of Laws and Parsons (1943) by Van Dijk et al. (2002)

\[ KE = \text{Area} \cdot \kappa \cdot R^{n+1} \cdot \Delta t \]

where \( \kappa = 13; n=0.191; \) Area=surface area (m²) receiving a given rainfall intensity; and \( \Delta t = \) time increment (one-sixth of an hour in our case). While many different functions relating intensity to kinetic energy have been proposed, recent work suggests that a power law is the most appropriate (Salles et al. 2002).

### Table 3. Distribution of Reflectivity Values (Z) at Different Times for a Storm on July 20, 2002 [Shown in Fig. 1(b)]; Times (1510 CST, 1520 CST, etc.) Are in Central Standard Time

<table>
<thead>
<tr>
<th>Z</th>
<th>1510</th>
<th>1520</th>
<th>1530</th>
<th>1535</th>
<th>1540</th>
<th>1545</th>
<th>1550</th>
<th>1555</th>
<th>1600</th>
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<tr>
<td>0</td>
<td>0.82</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0.17</td>
<td>0.07</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.01</td>
<td>0.21</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>15</td>
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Note: In the analysis, we only looked at radar on 10-min intervals but here we look at 5-min intervals around the peak (~1535 CST) in order to better infer the delay between storm peak and discharge peak (1555 CST).

### Explaining Interstorm Variability in Particulate Loads

#### Model Development

Potential predictor variables of L were evaluated in various regression models to predict L across the 14 storms with radar data in the Spring Harbor watershed. However, some potential predictor variables are inherently correlated to L due to the way in which L is calculated. As seen in Eq. (7), L is dependent on the sum of a function of q over a storm event. Since precipitation drives runoff, the precipitation volume, total runoff volume, and average rainfall intensity will frequently be correlated with q and, consequently, L. A strong correlation resulting from the pairing of a variable and a function of that same variable is sometimes referred to as a spurious self-correlation (see Kenney 1982; Vogel et al. 2005; Shivers and Moglen 2008). In our analysis, because V is calculated as \( \sum q \cdot \Delta t \) [see Eq. (6)] and L is also a function of \( q \) [Eq. (7)], V and L may exhibit some amount of
self-correlation. However, for the data here, there is a statistically significant relationship between \( C \) and \( q \) following the form of Eq. (5) (as discussed earlier in the Methods section) that underlies the relation between \( V \) and \( L \). Shivers and Moglen (2008) have recently drawn attention to cases of self-correlation where \( V \) and \( L \) have a strong correlation and \( C \) and \( q \) have no correlation, which is not the case here. In addition to \( V \), we will also evaluate three other possible predictors: \( \text{KE}_{30} \), \( q_p \), and \( T_{\text{dry}} \).

To identify the primary factors influencing particulate wash-off (\( L \)), we evaluate several model formulations. Linear models relating \( \ln(L) \) to \( \ln(\text{KE}_{30}) \) and \( \ln(L) \) to \( \ln(V) \) resulted in \( R^2 \) values of 0.19 and 0.69, respectively (see Models 2 and 4 in Table 4). However, a multivariate model

\[
\ln(L) = a + b \cdot \ln(V) + c \cdot \ln(\text{KE}_{30}) + \epsilon \tag{9}
\]

resulted in an even better \( R^2 \) of 0.81. Logarithms provided homoscedasticity among the errors, \( \epsilon \). Despite the fact that \( \ln(V) \) explains much of the variation in the model given by Eq. (9), the addition of \( \ln(\text{KE}_{30}) \) adds to the prediction of \( \ln(L) \) and is significant at the 2.4% level. Table 4 summarizes \( R^2 \) values, parameters, and \( p \)-values (calculated for a two-sided \( t \)-statistic) of the significance of each parameter within each model. Actually, a one-sided \( t \)-test can be justified because \( L \) should increase with both \( V \) and \( \text{KE}_{30} \), allowing the \( p \)-values in Table 4 to be halved. Fig. 4 shows the residuals associated with the three models; as would be expected, the model in Eq. (9) consistently results in smaller residuals than use of \( \ln(V) \) or \( \ln(\text{KE}_{30}) \) alone.

A model similar to Eq. (9) in which \( \text{KE}_{30} \) is replaced by \( T_{\text{dry}} \) resulted in an \( R^2 \) value of 0.69 (model 5 in Table 4), the same result as using \( V \) alone (Model 4 in Table 4). Note, a model of \( T_{\text{dry}} \) alone (Model 1) results in an \( R^2 \) value of only 0.04. For the Spring Harbor watershed, this result suggests that antecedent dry days play little role in explaining variability in \( L \).

A model similar to Eq. (9) in which \( \text{KE}_{30} \) is replaced by \( q_p \) (Model 7 in Table 4) resulted in \( R^2 = 0.77 \); a statistical test on the \( c \) coefficient indicated that the addition of \( \ln(q_p) \) barely adds to the prediction of \( \ln(L) \) (\( p \)-value of 0.08 for a two-sided test). While the significance would frequently be rejected at the 5% level or less, the relatively small data set made us hesitant to dismiss the outcome outright.

Given that \( q_p \) is moderately correlated to \( V \) (\( r = 0.80 \)), it is somewhat surprising \( q_p \) adds any explanatory power beyond \( V \) in the multiparameter model. Furthermore, \( q_p \) and \( \text{KE}_{30} \) are not highly correlated (\( r = 0.61 \)), suggesting that \( q_p \) aids in predicting \( L \) for different reasons than \( \text{KE}_{30} \). A large \( q_p \) could possibly result from either intense rainfall (and sizable kinetic energy input) or wet antecedent soil moisture conditions. Obviously, higher intensity would enhance particulate loss but the role of wetter antecedent conditions on particulate loss is unclear. Therefore, certain changes in the magnitude of \( q_p \) may be unrelated to changes to \( L \), resulting in its diminished predictive value in comparison to \( \text{KE}_{30} \) and the weak significance of \( q_p \). This is seen in our qualitative example in Fig. 1 where the same \( q_p \) is associated with different TSS concentrations.

**Evaluation of Buildup/Wash-Off Models**

The regression models in the previous section suggested that the magnitude of particulate load in storm water is not explained by antecedent dry days (\( T_{\text{dry}} \)). However, BUWO models are specifically formulated to use \( T_{\text{dry}} \) to predict loads. Thus, we ask why

![Fig. 4. Residuals from three different regression models: a model including \( \text{KE}_{30} \) and \( V \) as variates (filled circles, \( R^2 = 0.81 \)), a model only including \( \text{KE}_{30} \) (open triangles, \( R^2 = 0.19 \)), and a model only including \( V \) (cross symbols, \( R^2 = 0.69 \))](image-url)
BUWO models have proved suitable in application despite the failure of \( T_{\text{dry}} \) to predict loads (Charbeneau and Barrett 1998; Sutherland and Jelen 2003; Vaze and Chiew 2003). From the regression models we saw that for a given storm, \( L \) is closely correlated to \( V \). A process model assuming CAM [e.g., Eq. (2)] functionally assumes all variation in \( L \) is dependent on \( V \) and none on \( T_{\text{dry}} \). In this section we evaluate under what circumstances BUWO models could be simplified to a wash-off model with the CAM model.

### Applying a Buildup/Wash-Off Model to the Spring Harbor Catchment

Here, we compare the particulate loads estimated directly from a BUWO model [Eq. (1)] and CAM model [Eq. (2)] to observed loads from the 19 consecutive storms in the Spring Harbor watershed. Compared to the regression models, this is a more rigorous assessment of the role of antecedent dry days because the BUWO model accounts for the full history of the BUWO sequence. \( T_{\text{dry}} \) in the regression models only reflects the time since the last storm event occurred and does not account for the magnitude of the previous rain. Large storms may have been preceded by very small storms that reset \( T_{\text{dry}} \), but which did not remove a large amount of particulate.

Fig. 5 shows the observed event loads, the simulated loads from the best-fit BUWO model, and the simulated loads from the best-fit CAM model. From Fig. 5, we see that the primary differences between modeled and observed loads occur with the May 28, 2002 event near cumulative Day 30 and the August 21, 2002 near cumulative Day 90. The observed loads on both these days are much larger than predicted by either model. Because of these discrepancies, the BUWO model had a \( R^2 \) of only 0.26 while the CAM model had an \( R^2 \) of just 0.07. As indicated in Table 1, these large observed event loads correspond to neither the largest discharge volumes nor the longest antecedent dry period, the only drivers on which the models are dependent.

This outcome is somewhat surprising considering the relatively strong link between \( V \) and \( L \) found in the previous section. However, if we remove the two largest loads from the model output and recalculate the \( R^2 \), the \( R^2 \) for the BUWO model becomes 0.42 and the \( R^2 \) for the CAM model becomes 0.46, indicating the dependency of \( L \) on \( V \) holds for most events in the sequence. This again suggests \( T_{\text{dry}} \) is unimportant, given the similarity between the CAM (which is not dependent on \( T_{\text{dry}} \)) and BUWO models (which is dependent on \( T_{\text{dry}} \)). Unfortunately radar data were not available for these two anomalous events (May 28, 2002 and August 21, 2002); clearly these storms are instances where \( K_{\text{Eq}} \) or some other factor is critically important to estimating \( L \). Our penultimate section discusses possible stochastic pollutant inputs into systems that limit the accuracy of deterministic models.

Although some events in our dataset were not well explained by a BUWO or CAM model, the literature suggests many other observed sequences of storm event loads can be. In the remainder of this section, we assess if several successfully applied BUWO models reported in the literature (Chen and Adams 2007; Easton et al. 2007; Butler and Davies 2000) are equivalent to CAM models.

### Relating Constant Available Mass and Buildup/Wash-Off Models

To obtain more general insight into similarities in output from BUWO and CAM models, we compare various model parameterizations to determine when the BUWO and CAM models may generate similar load predictions. Specifically, we calculate the correlation \( (r) \) between output from BUWO and CAM models for a range of \( k' \) (\( k/m_0 \)) and \( \alpha \cdot E[Q_A] \) values selected from the literature (Chen and Adams 2007; Easton et al. 2007; Butler and Adams 2000), where \( E[Q_A] \) is the average daily runoff amount over a year \( E[Q_A]=\sum q\Delta t/\sum \Delta t \). We use \( k' \) (instead of just \( k \)) to make the comparison independent of \( m_0 \). In essence, \( m_0 \) scales the absolute magnitude of the wash-off and buildup processes, but \( m_0 \) is not important in assessing the correlation between BUWO and CAM models. We use \( \alpha \cdot E[Q_A] \) (instead of just \( \alpha \)) because it is a more general parameter accounting for possible compensating effects between \( \alpha \) and \( E[Q_A] \) across different watersheds (e.g., a wet region with a small \( \alpha \) may be equivalent to a dryer region with a higher \( \alpha \)). We use \( E[Q_A] \) instead of \( E[V] \), the average storm runoff volume, because \( E[V] \) does not reflect the frequency of storms; it would be possible for a locale that has only a single storm a year to have an \( E[V] \) equivalent to a locale that has a storm each week.

Furthermore, over the long run particulate accumulation and loss must balance, so that from Eq. (2)

\[
0 = k\left(1 - \frac{E[M]}{m_0}\right) - \alpha \cdot E[M] \cdot E[Q_A] \tag{10}
\]

where \( E[M] \) = long-term mean \( M \). When neglecting cross correlations between \( Q_i \) and \( M_r \), Eq. (10) results in

\[
\frac{E[M]}{m_0} = \frac{k'}{k' + \alpha \cdot E[Q_A]} \tag{11}
\]

Thus, Eq. (11) clearly shows that the average magnitude of \( M \) over multiple storm events in a BUWO model should be dependent on \( k' \) and \( \alpha \cdot E[Q_A] \) and that these are the most relevant terms to consider across multiple model parameterizations.

We evaluated 300 unique sets of \( k' \) and \( \alpha \cdot E[Q_A] \) for both the BUWO [Eq. (1)] and CAM [Eq. (2)] models using the historical discharge time series from the Spring Harbor catchment as the driver. For each of the 300 paired simulations, the CAM model uses the same \( \alpha \) as the BUWO model; the CAM model is inde-
Simulations are driven by 2002 discharge data from the Spring Harbor catchment. Other catchments may have different roughness characteristics. The quantity \( r \) was calculated on the loads estimated by the BUWO and constant mass models for the 19 summer storm events during 2002 in the Spring Harbor catchment. For the Spring Harbor catchment, \( E[Q_a] = 1.12 \text{ mm day}^{-1} \). Other catchments may have different \( E[Q_a] \) but we assume the combined product of \( \alpha \cdot E[Q_a] \) is the relevant parameter (as explained earlier), not \( E[Q_a] \) alone.

Fig. 6 shows contour lines of \( r \) for a plot of \( \alpha \cdot E[Q_a] \) (day\(^{-1}\)) versus \( k^* \) (day\(^{-1}\)). The quantity \( k^* \) is the rate constant for particulate buildup. Given that storms in northern temperate regions of the United States occur about once per week, \( k^* \) of greater than unity implies that particulate material should nearly always buildup to the surface maximum, \( m_{po} \), before the next storm. In such a case, there would be little difference between a BUWO model and a CAM model. As shown in Fig. 6, when \( k^* > 1 \text{ day}^{-1} \), \( r \) approaches 1.

The quantity \( \alpha \cdot E[Q_a] \) is the rate constant of average daily particulate loss. \( \alpha \cdot E[Q_a] \) can be large when either \( \alpha \) or \( E[Q_a] \) is large. Large \( E[Q_a] \) results from sizable annual runoff due to either frequent rainfall or a high density of impervious surface in the catchment. Alternatively, large \( \alpha \) implies the surface readily loses particulate (due to the nature of the particulate or surface roughness characteristics). If \( \alpha \cdot E[Q_a] \) is less than 0.1 day\(^{-1}\), there is little loss with each storm event and available particulate remains near an equilibrium value. In this case, again, there would be little difference between a BUWO model and a CAM model. As shown in Fig. 6, when \( \alpha \cdot E[Q_a] < 0.1 \text{ day}^{-1} \), \( r \) approaches 1.

When \( \alpha \cdot E[Q_a] < 0.1 \text{ day}^{-1} \), event loss becomes sizable and the available particulate mass can vary greatly between storm events. Only if \( k^* \) is commensurately increased will mass recover enough between storms so that the available mass at the beginning of each storm event remains relatively constant. Thus, to keep the same \( r \) with an increasing \( \alpha \cdot E[Q_a] \), one must also increase \( k^* \), as seen in Fig. 6. We provide an illustration of this interplay between \( k^* \) and \( \alpha \cdot E[Q_a] \) in Fig. 7.

Fig. 7 presents the magnitude of \( M_t \) over time for three different parameterizations of the BUWO model. The key feature to look at in each time series is the magnitude of \( M_t \), just before a downward drop marking a wash-off event. For the simulation resulting in \( r=0.85 \) (\( k^*=0.03 \text{ day}^{-1} \); \( \alpha \cdot E[Q_a]=0.12 \text{ day}^{-1} \)), the preevent \( M_t \) remains relatively close to 5 kg. Keeping \( k^* \) constant and increasing \( \alpha \cdot E[Q_a] \) results in a simulation of \( r=0.23 \) (\( k^*=0.03 \text{ day}^{-1} \); \( \alpha \cdot E[Q_a]=0.40 \text{ day}^{-1} \)) where the preevent \( M_t \) fluctuates more widely. However, by increasing \( k^* \) to 0.58 day\(^{-1}\) while maintaining \( \alpha \cdot E[Q_a]=0.40 \text{ day}^{-1} \), \( M_t \) fluctuations decrease and \( r=0.80 \). More quantitatively, the coefficient of variation of preevent \( M_t \) values for the \( r=0.85 \) and \( r=0.80 \) simulations are 0.30 and 0.19, respectively, while the coefficient of variation for the \( r=0.23 \) simulation is 0.57. This comparison of the coefficient of variation values clearly indicates greater relative variability in the preevent \( M_t \) of the \( r=0.23 \) simulation.

In brief, given the frequency of storms in the northern temperate region of the United States if a BUWO model is parameterized so that buildup between storms is very rapid (\( k^* > 1 \text{ day}^{-1} \)) or that wash-off is small (\( \alpha \cdot E[Q_a] < 0.1 \text{ day}^{-1} \)), the BUWO model will closely resemble a CAM model. In an intermediate range, the two models may or may not produce relatively similar predictions depending upon the relative values of the two parameters as illustrated in Fig. 6.

Assessing Buildup/Wash-Off Parameterizations in the Literature

We can use the relationships established in our Fig. 6 contour plot to assess whether the use of BUWO models reported in the literature could have been replaced by simpler CAM models. These literature-reported models were of the continuous exponential
form [Eq. (4)]. However, since Eqs. (1) and (3) are nearly equivalent when $\Delta \tau$ is small, we use the relationships in Fig. 6 developed using simulations based on Eq. (1) with $\Delta \tau$ between 5 and 15 min. Additionally, we assume the arrival time of storms in these other watersheds is reasonably similar to that of the storm events in the Spring Harbor watershed. Driscoll et al. (Driscoll et al. 1989, Table 4-3) reported the average number of storm events (55 year$^{-1}$) and the arrival times between storms (7 days) in the north central region of the United States. Driscoll’s average values compare favorably with those for the Spring Harbor storm sequence (46 year$^{-1}$ occurring every 9 days), indicating the sequence is relatively representative of other humid, temperate regions.

Chen and Adams (Chen and Adams 2007, Table 3) used $k^*=0.024$ mm day$^{-1}$ and $k=0.0112$ mm$^{-1}$ for modeling TSS wash-off in Ontario, Canada (these parameters are referred to as QFACT2 and RCOEF, respectively, in Chen and Adams 2007). The mean daily discharge was estimated as 0.40 mm day$^{-1}$ (Chen and Adams 2007, Table 1—mean rainfall, and Table 2—median runoff coefficient); resulting in $\alpha \cdot E(Q_A)= 0.044$ day$^{-1}$. Evaluating against Fig. 6, we find the combination of parameters is near the bottom of the chart, clearly in a range where $r$ approaches one.

Butler and Davies (2000) suggested ranges of $k=0.2$–0.4 day$^{-1}$ and $\alpha=0.1$–0.2 mm$^{-1}$ for use in Britain. Assuming 50% of the annual rainfall of 600 mm is converted to direct runoff in highly urbanized areas as based on typical Rational Method coefficients (ASCE 1996), $E(Q_A)$ is approximately 0.80 mm day$^{-1}$. The values of $\alpha \cdot E(Q_A)$ would range from 0.080 to 0.160 day$^{-1}$. Evaluating against Fig. 6, the range of parameters used by Butler and Davies (2000) results in $r$ values of 0.75 when $k^*$ approaches 0.4 day$^{-1}$. This indicates that in many typical parameterizations in Britain, the CAM model would perform relatively similarly to a BUWO model.

Easton et al. (2007) used $k^*=6$ day$^{-1}$ and $\alpha=0.02$ m$^{-1}$ for modeling total dissolved phosphorus wash-off in central New York. While Easton et al. (2007) do not specifically model TSS, it is one of the few cases in the literature where the parameters associated with a BUWO model are fully reported, and we assume it is reasonably representative of how BUWO models are applied by others in practice. Based on pictorial information presented in Easton et al. (2007, Fig. 3), we assume a mean discharge of 0.001 m day$^{-1}$, thus $\alpha \cdot E(Q_A)=0.0002$ day$^{-1}$. Evaluating against Fig. 6, we find the combination of parameters is off the bottom of the chart in a range where $r$ approaches one, as expected given that $k^*$ is so much greater than 1 day$^{-1}$. Thus, all three examples have parameter sets in a range where BUWO models generate similar output as CAM models.

### Discussion

A moderate amount of variability remains unexplained in the wash-off model given by Eq. (9) ($R^2=0.81$). Additionally, unidentified processes limited our ability to model the sequence of 2002 storm events. These confounding factors may originate from a number of sources: sample mishandling, the finite number of samples used to construct rating curves for load estimates, failure of radar to represent actual rainfall kinetic energy at ground level, finer scale spatial and temporal variability than detected by the radar, or stochastic inputs of particulate matter.

This final error source—stochastic inputs of particulate—raises the question of how and where materials buildup in urban landscapes. In particular, we do not believe that the available mass is truly constant in urban landscapes, despite the similarity between BUWO and constant mass models under certain parameterizations. Instead, we would suggest that buildup is not deterministically related to antecedent dry days. For instance, buildup is surely dependent on such unpredictable occurrences as construction work or the input of vegetative debris from wind storms. Buildup is unlikely to occur at a steady rate each day. Additionally, in a watershed with a storm drainage network, in addition to particulate buildup on surfaces such as pavement, there is likely to be temporary storage within pipes, catch basins, junction boxes, and other infrastructure (see Ashley et al. 1992; Reeves et al. 2004; Selbig and Bannerman 2007). Flushing of this accumulated material is likely to depend on a complex interaction between the amount and composition of the stored material and hydraulic processes in the pipe network. Either unpredictable inputs or sporadic flushing of the pipe network could account for the large unexplained loads, such as those seen in the sequence of 2002 storm events.

This study suggests that there are clearly important processes at work in urban sediment transport fate that are not accounted for in current wash-off models. Some of these may be highly stochastic or nearly unpredictable, such as interstorm airborne deposition, and will likely challenge the predictive power of deterministic, processes-based models. An evaluation of the uncertainty in a sewer water quality model applied in a watershed in Brussels found the model had no greater predictive capacity than the random drawing of pollutant concentrations from a probability distribution (Willems 2006). This suggests that if any kind of stochastic process is involved, one can only make reliable estimates over a time frame long enough to allow the stochastic inputs to converge to a relatively stable mean in the running average.

### Conclusions

We carried out two different analyses on a dataset of TSS concentrations in storm water from a watershed in Madison, Wis. First, a regression analysis compared several models and found that the particulate load from storm events is best explained by the combination of event runoff volume and rainfall kinetic energy ($R^2=0.81$). Event runoff volume alone explained the majority of the variation in particulate load between events ($R^2=0.69$).

In our case, underlying this strong correlation between runoff volume and load is a statistically significant relationship between concentration and discharge. Antecedent dry days, a traditional factor employed to explain variability in particulate load, had little explanatory value. The peak discharge in conjunction with runoff volume explained 77% of the variability in loads, but was only marginally significant (two-sided $p$-value = 8%). It appears $KE_{30}$ can potentially capture important differences in storm events not apparent from aggregate measures of storm events such as total volume, total rainfall, or average rainfall intensity.

As a second analysis, an extensive simulation study examined when a BUWO model yielded results similar to a CAM model. A contour plot related $k^*$ and $\alpha \cdot E(Q_A)$ to the correlation between BUWO and CAM models to allow a simple assessment of whether buildup actually needs to be included in a BUWO model. We evaluated parameter sets from calibrated BUWO models for watersheds in Ontario, Canada; central New York; and Britain. In two of the three cases the reported parameter values were in a range for which the BUWO models effectively functioned as
CAM models while in the third case the correlations were generally high. While these results are not definitive, they suggest that modelers in the future should check if the additional complexity of BUWO models is actually warranted by their data.

Despite various lines of evidence indicating $T_{av}$ has little value in explaining variation in particulate storm loads, BUWO models are still widely used. Our limited assessment of BUWO models suggests they do not necessarily lead to unrealistic results. Our generalized comparison of BUWO and CAM models using them since they do not necessarily lead to unrealistic results. Our generalized comparison of BUWO and CAM models suggests that BUWO models have in many cases been parameterized to behave similarly to a model with constant mass availability. By eliminating the buildup component, particulate loss could be simulated with a one parameter constant mass model ($\alpha M_{avg}$) instead of a three parameter BUWO model ($k, \alpha, m_0$). Such simplification is consistent with recent efforts to identify dominant processes (Sivakumar 2004) in order to avoid problems of nonidentifiability and undue uncertainty in model predictions (Sivapalan et al. 2003).

References


Analysis of storm event characteristics for selected rainfall gauges throughout the United States, EPA, Washington, D.C.


