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Research article

An urban runoff model designed to inform stormwater management decisions

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ABSTRACT

We present an urban runoff model designed for stormwater managers to quantify runoff reduction benefits of mitigation actions that has lower input data and user expertise requirements than most commonly used models. The stormwater tool to estimate load reductions (TELR) employs a semi-distributed approach, where landscape characteristics and process representation are spatially-lumped within urban catchments on the order of 100 acres (40 ha). Hydrologic computations use a set of metrics that describe a 30-year rainfall distribution, combined with well-tested algorithms for rainfall-runoff transformation and routing to generate average annual runoff estimates for each catchment. User inputs include the locations and specifications for a range of structural best management practice (BMP) types. The model was tested in a set of urban catchments within the Lake Tahoe Basin of California, USA, where modeled annual flows matched that of the observed flows within 18% relative error for 5 of the 6 catchments and had good regional performance for a suite of performance metrics. Comparisons with continuous simulation models showed an average of 3% difference from TELR predicted runoff for a range of hypothetical urban catchments. The model usually identified the dominant BMP outflow components within 5% relative error of event-based measured flow data and simulated the correct proportionality between outflow components. TELR has been implemented as a web-based platform for use by municipal stormwater managers to inform prioritization, report program benefits and meet regulatory reporting requirements (www.swtelr.com).

1. Introduction

1.1. Modeling stormwater impacts and BMPs

Hydrologic impacts associated with urban development are well documented and include declines in downstream receiving water quality (Arnold and Gibbons, 1996; Holman-Dodds et al., 2003; USEPA, 2013). Higher peak flows and increased total stormwater runoff volumes result from the expansion of urban impervious cover that limits the infiltration of rainfall and enhances the entrainment and transport of sediment, nutrients, bacteria, metals, pesticides, and other pollutants (Grove et al., 2001; Tang et al., 2005; USEPA, 2013). As a result of the 1972 Clean Water Act (CWA), the National Pollutant Discharge Elimination System (NPDES) and associated municipal separate storm sewer system (MS4) permits require that stormwater management programs protect downstream surface water quality and reduce pollutant discharge to the maximum extent practicable (USEPA, 2014). Municipalities implement structural controls (or structural best management practices (BMPs)) to reduce runoff and associated non-point source urban pollutant loading to receiving waters through infiltration and treatment of stormwater. These include small-scale decentralized low impact development (LID) and green infrastructure BMPs such as infiltration or bio-retention features, as well as larger scale centralized BMPs such as dry basins or treatment vaults (Brander et al., 2004; Bedan and Clausen, 2009; Gilroy and McCuen, 2009; Ahiablame et al., 2012).

California municipalities and regulators lack a comprehensive approach to prioritize where BMP implementation may have the greatest receiving water benefits and to assess progress towards stormwater and pollutant load reduction goals. Prioritization requires a reliable and consistent way to represent the relevant urban drainage attributes that contribute to runoff production irrespective of natural variability. Water quality monitoring to quantify urban stormwater impacts on receiving waters and runoff

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reduction effectiveness is a common NPDES permit requirement across the United States (e.g., California State Water Quality Control Board, 2013; Maryland Department of the Environment, 2013; State of Washington Department of Ecology, 2013), but there are significant practical challenges to using monitoring data to define priorities or reliably quantify the effectiveness of conservation efforts (Tomer and Locke, 2011). Monitoring costs severely limit the spatial and temporal extent of measurements relative to management information needs for reporting to regulators and making resource allocation decisions (Maheepala et al., 2001). Monitoring designs commonly fail to maximize the ability to detect changes distinct from natural variations (Karr, 1999). One key problem is the lag time between the implementation of BMPs and a measurable response in the receiving waters that can be detected above the hydrologic variability present in a stormwater system (Meals et al., 2010). Since our ability to detect changes in stormwater systems due to management actions is generally poor (Harmel et al., 2006; Rode and Suhr, 2007; Dotto et al., 2014), immediate use of monitoring data to guide implementation decisions and stormwater program adjustments is very limited.

Modeling provides a means to estimate stormwater reduction benefits of structural and non-structural BMPs, and test heuristic management scenarios to inform both short-and long-term stormwater programmatic planning decisions (e.g., Elliot and Trowsdale, 2007; Zoppou, 2001; Lee et al., 2012; Rossman, 2013; Voskamp and Van de Ven, 2015). Estimating event-based loads and concentrations in urban landscapes is complex, with timing that depends on wash-off effects that can vary between storms and even throughout the same storm based on pollutant species and land use (Lee and Bang, 2000). Model representation of such effects via continuous simulation requires data to characterize and parameterize these processes, but these data are generally unavailable or require an expert user to fit the model to observed data.

One would expect that over the long term, effective management actions that minimize runoff volumes and restore natural hydrologic functioning to urban environments will also minimize entrainment and delivery of urban pollutants to receiving waters (e.g., Walsh et al., 2016). Storm flows have been suggested by the National Research Council as a cost effective way to estimate pollutant loading (NRC, 2009) and have been used as a surrogate for pollutant loads in the Eastern US states (EPA Region 3, 2003). Given strong empirical associations between long-term urban pollutant loading, precipitation factors and drainage areas (Brezonik and Stadelmann, 2002), a simple approach that adequately characterizes precipitation and urban drainage conditions can help municipalities to comply with the statutory requirements of the CWA.

1.2. Study setting and objectives

In this paper we present a practical stormwater runoff model, the Tool to Estimate Load Reductions (TELR) specifically designed to be used by stormwater managers to inform annual program decisions and estimate the effectiveness of stormwater management actions across a municipality year after year. We compared TELR outputs with measured data from continuously monitored urban catchments in Lake Tahoe, California, as well as SWMM-based continuous simulation models to assess its adequacy as a planning tool. Runoff from urban catchments are a key driver of clarity loss in Lake Tahoe which threatens the aesthetics of this large subalpine ultra-oligotrophic lake (Schuster and Grismer, 2004); and stormwater managers are tasked with demonstrating progress towards runoff and pollution reduction goals. While only the hydrologic basis of the model is presented here, it should have direct utility for estimating long-term urban catchment pollutant loads by coupling runoff outputs with a basic pollutant module (such as the Simple Method of Schueler, 1987). Our approach simplifies the details of event-based process representation to align with the data commonly available to stormwater managers (the intended model users) and avoids site specific calibration required with most empirical and numeric approaches which adds to modeling costs and often introduces additional uncertainty to runoff estimates.

We defined the first study objective in terms of annual runoff simulation performance: *1) Achieve adequate performance relative to measured catchment flows and produce comparable estimates to continuous simulation models.* Fit with the observed data was judged relative to a number of metrics that reflect different aspects of model performance. To reliably quantity stormwater reductions, modeled structural BMP flow components should exhibit significant responses to changes in BMP inputs that match our understanding of BMP function and observed measurements of infiltrated, treated, and bypassed flows. Thus, we defined the second study objective relative to BMP simulation: 2) *Assess the ability of TELR to quantify BMP performance* via *runoff sensitivity to BMP inputs and comparisons with observed BMP data.* Sensitivity was quantified by the significance of the regression slope coefficient between BMP inputs and runoff component outputs, and correspondence with the observed data were judged based on relative percent error.

1.3. Model alignment with management needs

The intended use of model outputs should ultimately guide model selection and the necessary degree of model complexity (Leavesley et al., 2002) and the least complex model that reliably meets the anticipated application is often preferable (Chandler, 1994; Rauch et al., 2002; Dotto et al., 2012). While detailed representation of physical hydrologic processes within continuous simulation models can improve simulation performance, this model performance comes at the expense of greater structural complexity, particularly in the case of spatially distributed models (Snowling and Kramer, 2001), without necessarily increasing the usefulness of outputs (Lindenschmidt, 2006). Inclusion of extraneous model components or parameters that do not result in a measurable output response may improve simulation performance, but can also make a model less useful for discerning hydrologic changes in a catchment over time (Beven, 2001; Nandakumar and Mein, 1997), or testing heuristic management scenarios (Freni et al., 2011). In relatively complex model alternatives, such as the widely used Storm Water Management Model (SWMM), there are numerous free parameters that usually require user calibration, while only a few input variables may contribute significantly to the outputs (Li et al., 2014). Over-parameterization results in a high degree of uncertainty in the model outputs due to subjective decisions required during the calibration process (Beven, 1989, 2001) of parameter values that may vary over time and space (Hossain and Imteaz, 2016). Even where good hydrological data are available, they are probably only sufficient to support reliable calibration of models of very limited complexity (Jakeman and Hornberger, 1993; Gaume et al., 1998).

Overly burdensome input data requirements for setup, calibration, and validation of models are a barrier for use by stormwater managers, who are often not modeling specialists. Most available stormwater modeling tools are either intended exclusively for expert users (e.g., Atchison et al., 2012), or do not provide an efficient method for modeling multiple catchments or generating spatial outputs (e.g., Rossman, 2013; Tetra Tech, 2011). Simpler approaches to hydrologic modeling may provide comparable performance to more complex ones for certain applications (e.g., Kokkonen and Jakeman, 2001; Perrin et al., 2001; Bormann and Diekkruger, 2003; Reed et al., 2004). Indeed, with the inclusion of some basic land-use data, uncalibrated models can reach comparable performance to more sophisticated calibrated models such as SWMM (Petrucci and Bonhomme, 2014). TELR is designed to have lower data input requirements than existing alternatives and be responsive to inputs that reflect management actions, such as installation of structural BMPs. By using a relatively simple approach that still meets performance needs of stormwater managers, our aim was to minimize uncertainty as well as lower costs associated with model development, operation, calibration, and long-term use.

2. TELR model description

2.1. Scales of representation

Selection of relevant scales for representation is important to quantify the benefits of BMP implementation over time in a meaningful way. Stormwater models vary widely in terms of how urban catchments are delineated and how landscape characteristics are discretized. TELR employs a semi-distributed approach, with the entire city area delineated into smaller drainages (catchments) of approximately 100 acres (40 hectares), within which landscape characteristics and process representation are lumped. To remain within this approximate size range, delineated catchments are often partial drainages, so that there may be runoff downstream from one catchment to another via stormwater infrastructure or channelized urban streams. Explicit routing across different land use types or features is not represented as it would be in fully distributed models (e.g. Bicknell et al., 1997; Lee et al., 2012), rather, attributes and BMPs are assigned to the proportions of different land use types within a catchment. Landscape attributes defined at the catchment level include area, land use, soil type, imperviousness, slope, and hydrologic connectivity to the receiving water.

Typically, stormwater runoff is modeled using 1 of 2 approaches: a single storm event methodology or a multi-year, high-resolution (daily or sub-daily) continuous simulation. Event-based approaches are programmatically simple but were originally designed to simulate runoff for a single storm event size (USDA-SCS, 1986). Continuous simulations are generally better able to capture the dynamic range of rainfall-runoff responses by accounting for antecedent catchment moisture conditions (Harbor, 1994; Bicknell et al., 1997; Rossman, 2008). TELR employs a hybrid event-based approach that combines a set of events drawn from a long-term regional precipitation distribution to provide average annual runoff estimates. This time resolution generally aligns with the information needs of stormwater managers and allows substantially simplified computation compared to continuous simulation.

2.2. Precipitation inputs

TELR precipitation inputs are designed to bracket the intra-annual and inter-annual variability demonstrated by historic data for several areas throughout the western US. We defined a set of 'precipitation regions' by examination of the spatially interpolated rainfall dataset published by PRISM Climate Group at Oregon State University (http://www.prism.oregonstate.edu/). We used the historic distribution of 24-hr rainfall depths (24-hr event frequencies) and the average annual number of days with measured rainfall to drive runoff generation. The 30-year precipitation cumulative distribution function for each climatic region was broken into a set of percentile values. This approach provides a way to bracket the likely event magnitudes in each region, incorporates extreme events in a manner proportional to their likelihood of occurrence, and serves to standardize the inputs from one modeling scenario to another using a small number of representative metrics.

We determined an appropriate number of metrics to use as inputs by comparison with precipitation data compiled by the Western Regional Climate Center, Cooperative Climatological Data Summaries (available online at: http://www.wrcc.dri.edu/climatedata/climsum/). We selected 3 locations in California, 2 in each of Nevada and Arizona, and 1 in Hawaii, in an effort to represent the range of applicable climatic conditions within US EPA Region 9, a regulatory jurisdiction composed of these four Pacific Southwest states (station details provided in Table 1). Our goal was to define a small number of 24-hr events to represent the rainfall distribution and accurately estimate total average annual depths. We calculated rain days, *d,* as the average number of days with precipitation >0.01 inches (0.25 cm) and, $P(x)$, the 24-hr event frequency estimate, where P is the 24-hr rainfall depth for the xth percentile event. On a water year basis, we selected 24-hr event rainfall frequencies and applied the trapezoid rule to estimate the integral of the 24-hr event cumulative distribution function to obtain a long-term average 24-hr runoff volume for days when it rains. We approximated the integral using the following equation for non-uniform intervals of x:

$$\int_0^{100} P(x)\,dx \approx \frac{1}{2}\sum_{k=1}^{N}(x_{k+1}-x_k)^*(P(x_{k+1})+P(x_k)) \tag{1}$$

where x is a number between 0 and 100, and k is number in the sequence of total, N, percentile events used to estimate the integral. To obtain a long-term average annual runoff volume, P_{365}, we multiplied the 24-hr average by the number of rain days per year, d:

$$P_{365} = d^*\int P(x)dx \tag{2}$$

We calculated the average annual 24 h rainfall for days when it rains using various numbers of 24-h event frequency breaks using quartiles (Approach 1), deciles (Approach 2) and a set of 4 percentile events that correspond with common municipal permit requirements and structural BMP design criteria (85th and 95th percentile storm events), which also included the median and the lower quartile (Approach 3). Fig. 1 shows the historic 24-hr event frequency distribution for a typical precipitation distribution and a graphical representation of how the trapezoid rule is used to estimate the long-term average 24-hr rain events. As expected for uniform grids, the estimates using the trapezoid rule improved when more percentile events were used. Approach 1 (quartiles) had an average error of −13% compared to Approach 2 (deciles), which had an average error of −3%. Approach 3 demonstrated a similar relative error as Approach 2, and since fewer percentile events were used and it includes those event frequencies relevant to structural BMP design requirements, we used this approach to create the standardized regional inputs for TELR.

2.3. Rainfall-runoff transformation

For a given storm magnitude and duration, the runoff generation module defines the fraction of flow that infiltrates over pervious surfaces and the fraction of overland runoff that is eventually discharged to the receiving waters. TELR relies on the Soil Conservation Service (SCS) curve number (CN) method and the approach detailed in Technical Release 55 (TR-55) to estimate

Table 1
Station metadata used in the development of regional daily precipitation approach. All stations reporting daily data from Oct 1, 1981 to Sept 30, 2014.

Site location	Abbreviation	COOP ID	Lat	Lon	Rain days
			ddmm	dddmm	>0.01 in (0.25 cm)
Las Vegas, Nevada	LAS	264432	3605	11510	21.6
Reno, Nevada	RNO	266779	3930	11947	41.5
Phoenix, Arizona	PHX	26481	3326	11201	31.1
Los Angeles, California	LAX	45114	3356	11823	31.7
Sacramento, California	SMF	47630	3831	12130	53.6
Flagstaff, Arizona	FLG	23010	3508	11140	76.2
Tahoe City, California	THC	48758	3910	12009	75.5
Lihue, Hawaii	LIH	515580	2159	15921	160.1
Eureka, California	ACV	42910	4048	12410	111.3

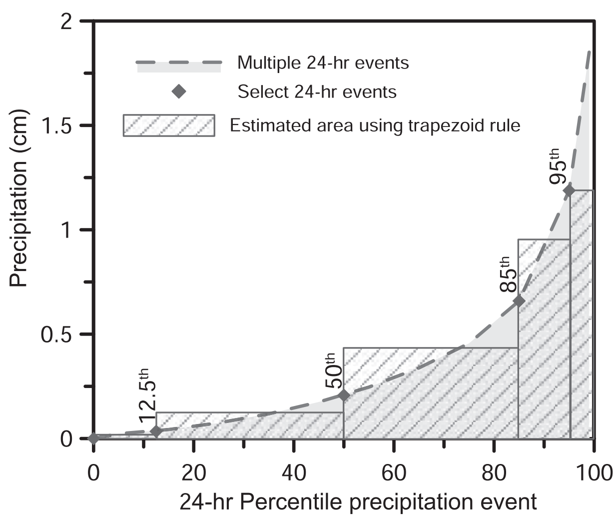

Fig. 1. Illustration of the trapezoid rule for estimating long-term average 24-hr rainfall using the frequency distribution of 24-hr precipitation events.

runoff from small urban catchments (USDA-SCS, 1986). The SCS runoff equation is:

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S} \tag{3}$$

where Q is the runoff depth, P is the 24-hr rainfall depth, S is the potential maximum retention after runoff begins, and I_a is the initial abstraction depth. The initial abstraction incorporates all losses before runoff begins, including water retained in surface depressions, water intercepted by vegetation, evaporation, and infiltration. Runoff does not begin until the initial abstraction has been met. I_a is variable across the landscape but is highly correlated to the curve number. The initial abstraction is 20% of the storage,

$$I_a = 0.2S \tag{4}$$

and

$$S = \frac{1000}{CN} - 10 \tag{5}$$

More recent data suggest that 0.20*S might be too high and that 0.05*S is more appropriate (Woodward et al., 2003; Lim et al., 2006; Shi et al., 2009) especially for hydrologic soil groups C and D (Jiang, 2001). If 5%, rather than 20%, is used, S must also be modified. The relationship between $S_{0.05}$ and $S_{0.20}$ obtained from model fitting results is (Lim et al., 2006; Hawkins et al., 2002)

$$S_{0.05} = 1.33{*}S_{0.20}{}^{1.15} \tag{6}$$

We used the adjusted initial abstraction ratio (equation (6)) and by substituting equation (4), modified for 5% of storage, into equation (3), we obtain

$$Q = \frac{(P - 0.05S_{0.05})^2}{P + 0.95S_{0.05}} \tag{7}$$

Curve numbers range from 30 to 98 and lower numbers indicate low potential runoff whereas higher numbers indicate increasing runoff potential. The major factors that determine SCS curve numbers are the soil type, the land use (specifically, the percent impervious of the land use), the hydrologic condition and soil infiltration capability. To simply accounting for variations in soil permeability and infiltration, the NRCS has classified soils into 4 hydrologic soil groups (HSGs). A curve number for a given land use with impervious area can be estimated by the following (USDA-SCS, 1986):

$$CN_c = CN_p + \frac{P_{imp}}{100}(98 - CN_p) \tag{8}$$

where CN_c is the runoff curve number for the entire land use, CN_p is the pervious runoff curve number and P_{imp} is the percent imperviousness.

The model generates discrete runoff outputs which mirror the 24-hr event percentile precipitation inputs. Using equations (1) and (2), we replaced the rainfall $P(x)$ with runoff $R(x)$, where R is the runoff calculated by the approach described above for a set of 24-hr rainfall events. Similar to the calculation described for the rainfall, the trapezoid rule is applied to the xth percentile event which are summed to approximate the area under the probability distribution function and obtain the average annual runoff.

Antecedent moisture conditions are a critical component to accurately determining runoff and the SCS curve numbers originally incorporated average antecedent runoff conditions (USDA-SCS, 1986). The ability of continuous models to represent varying catchment moisture condition is a distinct advantage over event-based models. Recent studies have shown the importance of adjusting CNs based on antecedent runoff conditions (Bhaduri et al., 2000; Michel et al., 2005). Because our tool was developed to estimate long-term average annual runoff conditions, we do not adjust the CNs and assume average antecedent runoff conditions for all simulations.

2.4. BMP representation

TELR was developed to easily incorporate both structural and non-structural stormwater BMPs of various types, sizes, and applications. Here, we present the model approach to large-scale centralized structural BMPs (e.g., treatment vaults, infiltration basins, dry basins), which typically treat stormwater runoff at a catchment outlet with capacities on the order of an acre-foot or approximately 1200 m^3. They typically treat much larger drainage areas than decentralized BMPs, such as bioretention systems or catch basins that are commonly distributed throughout urban catchments. Stormwater can exit a centralized BMP in 1 of 3 ways: soil infiltration, through a treatment aperture, or via bypass where no treatment or detention has occurred. Some models also include evaporative losses, but given proper functioning, structural BMPs should have drawdown times on the order of hours and we assume this term is negligible. Volume loss components depend on the BMP type and design specifics. For example, an infiltration BMP has only infiltrated and bypassed volumes, while a treatment vault has only treated and bypassed volumes since water is temporarily stored in a concrete chamber before flowing through a filtration media. Fig. 2 provides a schematic for an example dry basin, infiltration basin and treatment vault, from which TELR assumes volume loss via infiltration, treated outflow, and bypass.

TELR models centralized BMPs using the USDA TR-55 (1986) methodology for estimating peak inflow and peak outflow. Calculations for infiltrated, treated, and bypassed stormwater runoff volumes are completed for each prescribed 24-hr percentile storm event. Average annual infiltrated, treated, and bypassed stormwater volumes are estimated using the trapezoid rule and the average number of rain days per year.

Estimating of peak inflow discharge requires reasonable representation of the time of concentration, the time it takes from water to flow from the most remote part of the watershed to the watershed outlet. There are a number of different ways to estimate time of concentration (USDA-SCS, 1986; 2010). We selected a relatively simple formula (equation (15)–(4); USDA SCS, 2010) that could be easily implemented for a variety of urban catchments and required minimal additional inputs by the user. Time of concentration is estimated by the NRCS lag method as

$$T_c = \frac{l^{0.8} * (S+1)^{0.7}}{1140 * Y^{0.5}} \tag{9}$$

where T_c is time of concentration (hr) for average natural watershed conditions, l is the flow length (ft), Y is the average watershed slope (%), and S is the maximum potential retention from equation (5). Because the lag equation was developed for rural areas, it can overestimate the time of concentration for urban areas which have higher proportion of impervious area and channelized flow that allow water to through the catchment at a faster rate than under natural conditions. The following equation was applied to adjust the T_c calculated by the NRCS lag method (FHWA HEC-19, 1984)

$$T_c' = T_c * CF * IF \tag{9a}$$

where T_c' is the adjusted time of concentration, T_c is the time of concentration in hours from Eq. (9), CF is the channel improvement factor, and IF is the impervious area factor, both of which are estimated from the impervious area of the catchment.

Next, unit peak discharge, q_u, is computed based on T_c and SCS rainfall distribution type

$$\log(q_u) = C_0 + C_1 \log(T_c) + C_2[\log(T_c)]^2 \tag{10}$$

where C_0, C_1, and C_2 are the coefficients from Table F-I (USDA-SCS, 1986) based on the SCS rainfall distribution type. Rainfall distribution Type I pertains to all examples presented herein. Peak inflow

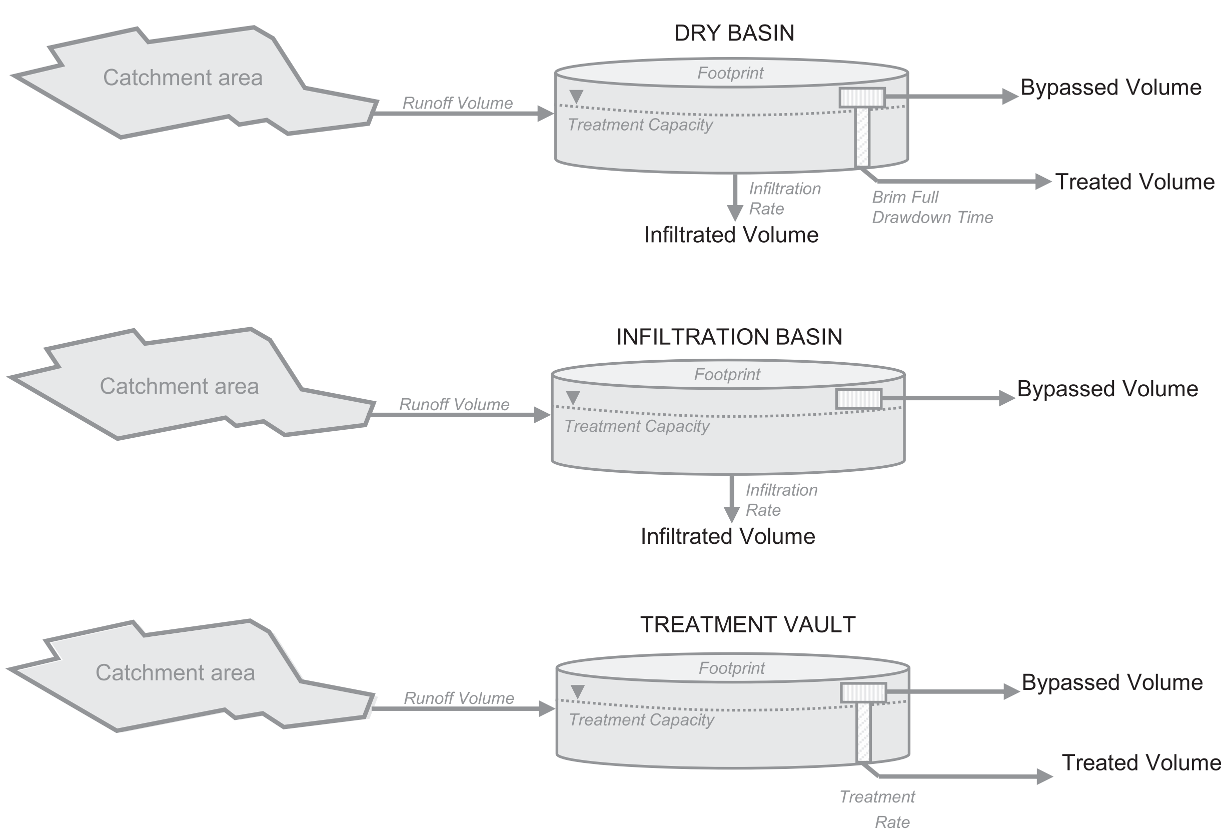

Fig. 2. Schematic overview of BMP modeling in TELR. Grey text indicates user inputs and black text indicates values calculated by the model (adapted from Northwest Hydraulic Consultants et al., 2009).

discharge, q_i is estimated as

$$q_i = q_u AQF_p \quad (11)$$

where A is drainage area, Q is runoff depth, and F_p is a ponding factor. Finally, estimation of the peak outflow discharge is

$$\frac{V_s}{V_r} = C_0 + C_1\frac{q_o}{q_i} + C_2\left(\frac{q_o}{q_i}\right)^2 + C_3\left(\frac{q_o}{q_i}\right)^3 \quad (12)$$

where V_s/V_r is the ratio of storage volume to runoff volume of the BMP, q_o/q_i is the ratio of peak outflow to peak inflow, and C_0, C_1, C_2, and C_3 are the coefficients from Table F-2 (USDA-SCS, 1986) based on the SCS rainfall distribution type. Fig. 3A shows the relationship between the storage-runoff volume ratio and the outflow-inflow discharge ratio. Fig. 3B shows the shape of the inflow and outflow hydrographs where peak flows are estimated from equations (11) and (12), respectively. The inflow and outflow duration is estimated from peak flow (q_i or q_o) and Q, using graphical methods and assuming conservation of volume.

TELR derives each volume loss term from the outflow hydrograph using a hydrograph separation approach to estimate the fraction of volume infiltrated, treated, and bypassed (Fig. 3C), based on treatment capacity, footprint, and, if applicable, the infiltration rate and drawdown time. The corresponding volumes are calculated using graphical methods. Separation of the infiltration volume is determined by drawing a horizontal line across the hydrograph at the infiltration flow rate, calculated as the product of the infiltration rate and the footprint with proper unit conversion. Separation of the treated volume is defined by drawing a horizontal line across the hydrograph at the treatment flow rate, estimated as quotient of the treatment capacity and the drawdown time with proper unit conversion. Both the infiltration volume and the treated volume are calculated as the area of the outflow hydrograph under the respective flow rates down to a zero flow rate. If the sum of the infiltrated and treated volumes is less than the total outflow volume, then the remaining volume is allocated to bypass. If the sum of the infiltrated and treated volumes is greater than the total outflow volume, then the treatment volume is reduced to accommodate the difference and the volumetric balance between inflow and outflow is retained.

3. Data and methods

3.1. BMP sensitivity

Sensitivity tests were conducted on the centralized structural BMP model results to assess the relative influence of the 4 primary user inputs - treatment capacity, footprint, infiltration rate, and drawdown time — on infiltrated, treated, and bypassed volumes. Non-standard units were used as inputs, since these are the units used by practitioners in the USA (metric units are included in the associated tables). Tests were conducted on a 50-acre (20-hectare) catchment with 50% imperviousness, typical for small to moderate sized municipalities in California. The catchment slope was 2% and catchment length was 1500 ft. (457 m), with hydrologic soil group B and precipitation inputs for the Santa Barbara Region of California. The manner in which treatment capacity, infiltration rate, and drawdown time were varied are tabulated in Table 2 and represent a range of typical BMP design criteria with a total of 15 individual tests conducted. Sensitivity of the different flow components was quantified by a test of the regression slope coefficients for each across the range of input values, with a significance threshold of 95% confidence.

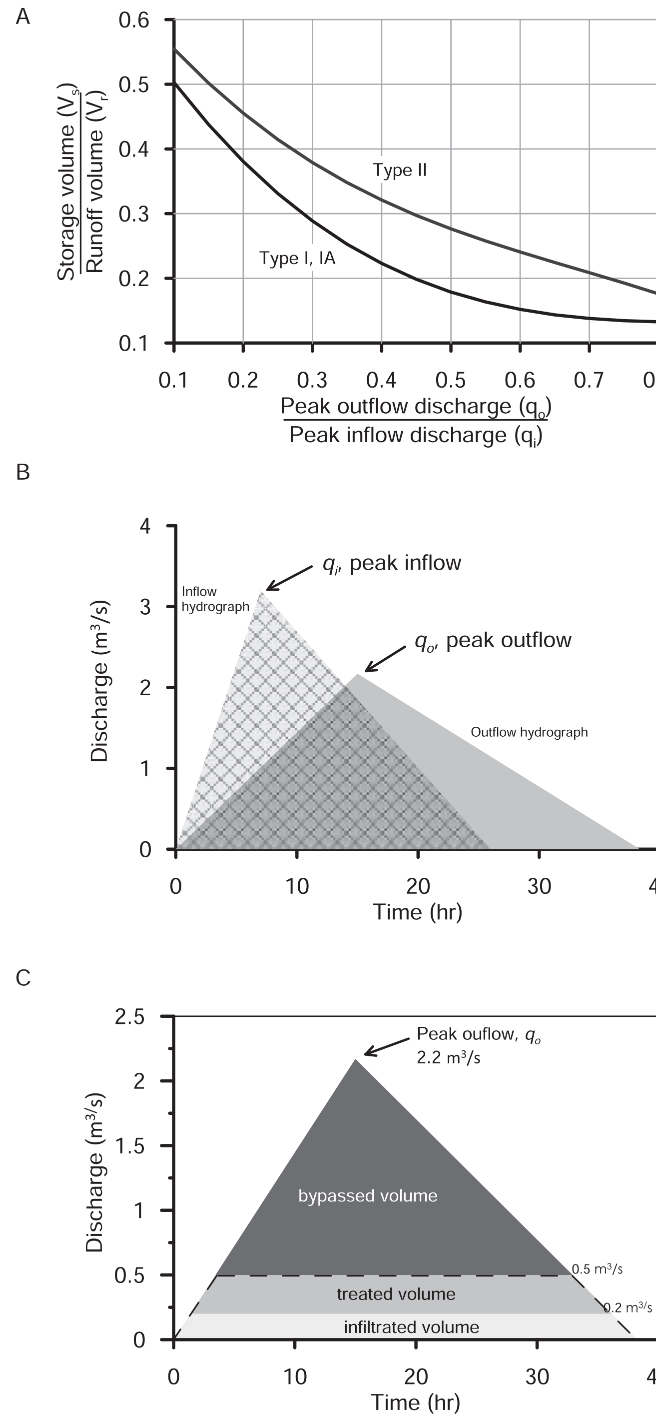

Fig. 3. TELR approach to modeling centralized BMPs using the USDA TR-55 method with hydrograph separation for infiltrated, treated, and bypassed volumes. A. Reproduced USDA TR-55 curves for estimating peak outflow discharge from peak inflow discharge, BMP storage capacity, and runoff volume. B. Conceptual comparison of inflow and outflow hydrographs assuming conservation of volume. C. Hydrograph separation approach for estimating infiltrated, treated, and bypassed volumes.

3.2. Conditional validation

We used data from in 6 urban catchments located in the Lake Tahoe Region of California and Nevada (Fig. 4) that were part of previous catchment monitoring and BMP effectiveness studies (2NDNATURE and Northwest Hydraulic Consultants, 2012, 2014).

Table 2
Inputs for centralized BMP sensitivity testing.

Treatment capacity ft^3 (m^3)	Footprint ft^2 (m^2)	Infiltration rate in/hr (cm/hr)	Drawdown time (hrs)
4500 (127)	900 (84)	0.05 (0.13)	48
18,000 (510)	3600 (334)	0.1 (0.25)	54
40,500 (1147)	8100 (753)	0.2 (0.51)	60
72,000 (2039)	14,400 (1338)	0.4 (1.02)	66
112,500 (3186)	22,500 (2090)	0.8 (2.03)	72

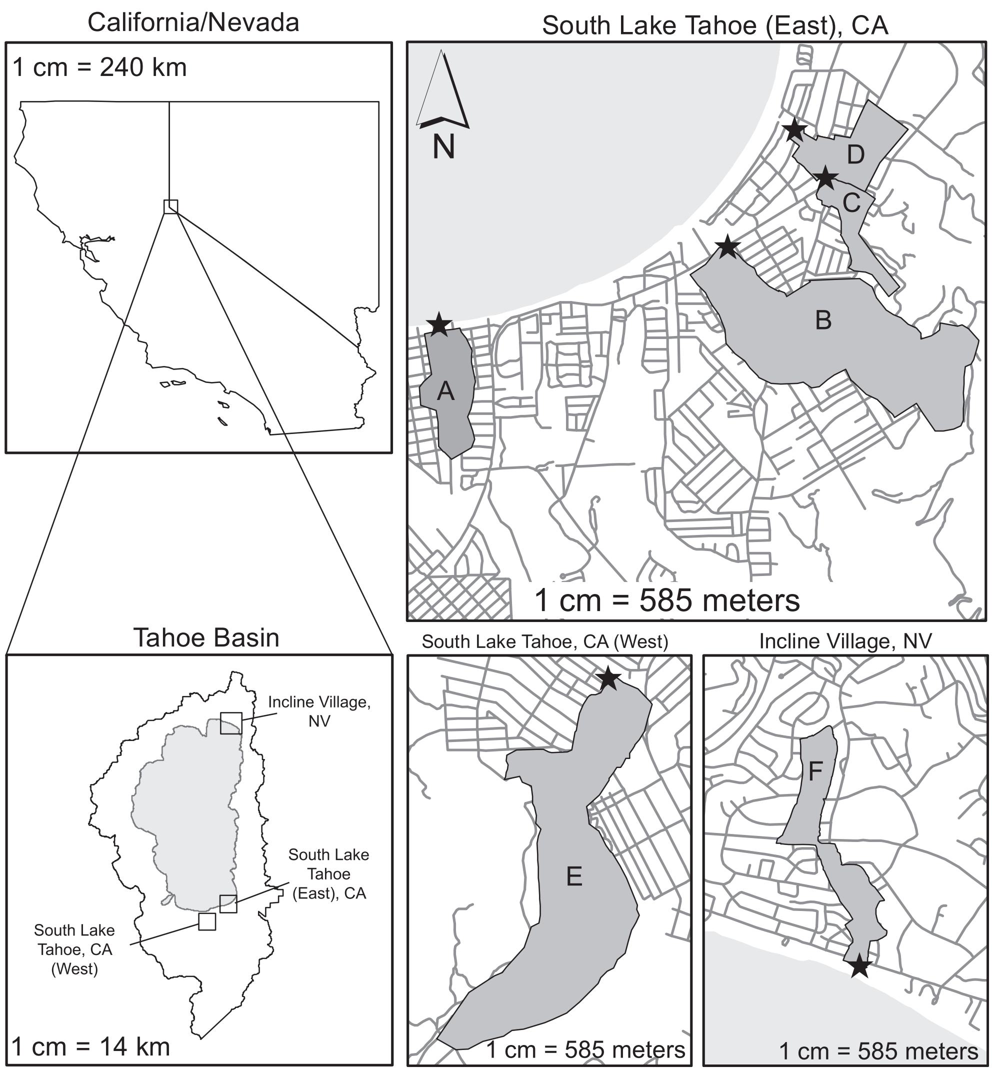

Fig. 4. Catchment and BMP locations of Pasadena (A), Osgood (B), Rocky Point (C), Park Avenue (D), and Eloise (E) in South Lake Tahoe, California and (G) in Incline Village, Nevada. Stars mark the catchment outlet locations.

These catchments receive snow in the winter, which is not explicitly represented in TELR, but since outputs evaluated were average annual runoff, and snow does not persist in these catchments into the fall, snow storage effects were assumed to be negligible. The authors installed automated instrumentation to measure on 10 min intervals the outflow for each catchment and the inflow, outflow and losses for each BMP. The pressure transducer data loggers were calibrated weekly and converted to discharge based on the site-specific hydraulics of the installation location. Instrument readings and calculations were compared to frequent manual depth and flow measurements (data reported in 2NDNATURE, 2010). Precipitation data from the local gauges listed in Table 3 were processed in the manner previously described in the Section 2.2 to generate the precipitation inputs for the time period corresponding to the period of measured flow data for each catchment. The relevant catchment characteristics are provided in Table 4. The impervious area of all catchments was adjusted based on proportion of disconnected impervious area (impervious runoff routed to permeable areas) for each land use type (as reported in 2NDNATURE and Northwest Hydraulic Consultants, 2014). Land use inputs are from local parcel assessor GIS layers and the percent impervious for each land use were validated by examination of satellite imagery and comparison to National Land Cover Dataset Percent Developed Impervious Layer (Xian et al., 2011).

Table 3
Metadata for precipitation stations in the Tahoe Basin used for validation experiments.

Precipitation site name (Catchment)	Station ID	Lat	Lon	Start date	End date
		ddmm	dddmm	YYYY/MM/DD	YYYY/MM/DD
City Lab (Eloise)	2NEL	3891	120006	2008/10/01	2011/09/30
DRI Diamond Peak (Incline)	DRI	3925	119924	2011/10/01	2013/03/01
Fire Station (Osgood, Park Avenue, Pasadena, Rocky Point)	CSLT	3894	119952	2013/10/01	2013/03/01

Table 4
Characteristics for Tahoe Basin test catchments. Data used in validation of centralized BMP approach.

	Osgood	Park avenue	Rocky point	Pasadena	Incline	Eloise
Size acres (ha)	341 (138)	225 (91)	169 (68)	71 (29)	117 (47)	540 (219)
Length ft (m)	7216 (2199)	1148 (350)	3280 (1000)	3346 (1020)	6299 (1919)	8185 (2495)
% Slope	9	7	10	3	23	40
Soil type	B	A	B	B	A	B
% Impervious	23	30	18	31	42	22
Avg. ann. precip in (cm)	17.3 (43.9)	17.3 (43.9)	17.9 (45.5)	18.4 (46.7)	20.7(52.6)	28.8 (73.2)

Since TELR operates on an average annual basis, and we had no more than 2 years of continuous flow data available for each catchment, the performance metrics were calculated on a regional basis which included all 6 of the test catchments in the Tahoe Basin. The percent bias PBIAS indicates a systematic offset of the model higher or lower than observations and is calculated for observed flows (Q_o) and modeled flows (Q_m) by equation (13).

$$PBIAS = 100\left[1 - \frac{\sum_i \left(Q_o^i - Q_m^i\right)}{\sum_i Q_o^i}\right] \tag{13}$$

The absolute percent bias (APBIAS) provides a measure irrespective of the sign of the errors which can may cancel each other out in the PBIAS calculation, resulting in low bias even when large errors actually occur. APBIAS is calculated in Eq. (14).

$$APBIAS = 100\left[1 - \frac{\sum_i abs\left(Q_o^i - Q_m^i\right)}{\sum_i Q_o^i}\right] \tag{14}$$

Similar to the coefficient of determination (R^2), the Nash-Sutcliffe Efficiency (NSE) measure (Nash and Sutcliffe, 1970) is a commonly used metric to evaluate hydrologic model performance (usually for continuous simulation) and is appropriate for comparisons between different periods or basins (Mathevet et al., 2006). The NSE ranges from -∞ to 1, with 1 denoting perfect agreement and 0 indicating that the mean observed value provides a better estimate than the model. The NSE measure was calculated as in Equation (15).

$$NSE = 1 - \frac{\sum_i \left(Q_o^i - Q_m^i\right)^2}{\sum_i \left(Q_o^i - \overline{Q_o}\right)^2} \tag{15}$$

The centralized BMP module was compared to measured BMP performance data for 5 events measured in 2 dry basins (Park Avenue and Rocky Point) and 1 wet basin (Osgood) within the City of South Lake Tahoe that represented a range of BMP sizes, event magnitudes, and antecedent runoff conditions (Table 5). Late summer and fall events were specifically chosen for this comparison to avoid snowfall and snowmelt effects, though, many of the rainfall events measured during the period of flow record either did not register inflow to the BMP or we were not able to confidently isolate a discrete event. To isolate the BMP module, the measured event flow volumes delivered the BMP were used as inputs (Table 5B). Infiltrated, treated, and bypassed volumes were estimated in TELR and compared to measured data for 24-hr periods and the relative percent error (RPE) between the observed flows (Q_o) and modeled flows (Q_m) was calculated for each flow component for each runoff event for as in Equation (16).

Table 5
Basin characteristics (A), and inflow volumes (B) for South Lake Tahoe BMPs.

A. BMP characteristics	Osgood	Park avenue	Rocky point
BMP Type	Wet basin	Dry basin	Dry basin
Treatment Capacity ft^3 (m^3)	3049 (86)	41,818 (1184)	11,761 (333)
Footprint ft^2 (m^2)	2250 (209)	27,600 (2564)	3000 (279)
Infiltration Rate in/hr (cm/hr)	0.04 (0.10)	0.25 (0.64)	0.15 (0.38)
Avg Treatment Rate ft^3/s (m^3/s)	0.07 (0.002)	0.38 (0.011)	0.25 (0.007)

B. Runoff events for BMP tests				
Date	24-hr precip in (cm)	Inflow ft^3 (m^3)		
		Osgood	Park Avenue	Rocky Point
Oct 8, 2009	0.31 (0.79)	–	–	2674 (75.7)
Oct 13, 2009	2.64 (6.71)	149,571 (4235)	2646 (74.9)	26,801 (759)
Oct 19, 2009	0.30 (0.76)	–	–	596 (16.9)
Jun 28, 2011	0.72 (1.83)	–	–	14,000 (396)
Aug 24, 2011	0.10 (0.25)	13,714 (388)	–	–

$$RPE = 100\left[\frac{(Qo - Qm)}{Qo}\right] \tag{16}$$

3.3. Model comparisons

Given the limited applicable runoff data available for small urban catchments, we also compared TELR runoff outputs to widely used continuous simulations models for a wide range of catchment characteristics. One of the most widely used urban continuous simulation models is the Environmental Protection Agency (EPA) Stormwater Management Model (SWMM), which provides detailed runoff simulation and has been used nationally and internationally for urban stormwater management applications. Two SWMM-based models were identified based on our familiarity with their use. The first SWMM-based model is EPA's National Stormwater Calculator (NSWC) (Rossman, 2013). The second SWMM-based model used was the Pollutant Load Reduction Model (PLRM) developed in partnership with the Lake Clarity Crediting Program for Lake Tahoe, California (Northwest Hydraulic Consultants et al., 2009). Both NSWC and PLRM are continuous simulation reservoir models that require catchment attributes, several user-specified parameter values, and a rainfall time series inputs to generate a continuous sequence of flows. Parameter values for PLRM and NSWC were not calibrated and were left at default values reported in EPA (2014) for the NSWC, and were specified from literature research during model development for PLRM (Northwest Hydraulic Consultants et al., 2015). Since NSWC rainfall data could not be adjusted or replaced, these data were sourced from the NSWC online database and were used as inputs to TELR for comparative purposes. Metadata for the central coast precipitation stations used is provided in Table 6. Results were compared on the average annual scale, due to output constraints from NSWC and PLRM. All catchment scale comparisons were conducted for catchments 100 acres (40.5 hectares) in size, with a 2% slope and no BMPs. We compared runoff estimates across all 4 HSGs, 3 locations, and a range of percent imperviousness (5%, 50%, and 95%) and calculated the coefficient of determination (R^2) to evaluate their correspondence.

4. Results

4.1. BMP sensitivity

TELR BMP input sensitivity tests confirmed that the model is generally consistent with observed flow separation processes for structural BMPs that both detain and infiltrate stormwater. All of the model flow components showed significant responses to treatment capacity. As the footprint and treatment capacity of the BMP increased, more stormwater runoff was treated and infiltrated so less runoff was bypassed (Fig. 5). When treatment capacity, footprint, and drawdown time were fixed, an increasing infiltration rate resulted in an increasing proportion of water infiltrated and a decreasing proportion of water bypassed (Fig. 5). For this situation, only the treated volume shows no significant response. The initial decline in the treated volume at low infiltration rates is the result of a shift in the ability to partially and then entirely infiltrate the 50^{th} percentile storm event. There is no change in the treated volume for infiltration rates greater than 0.2 in/hr (0.5 cm/h) in this example because there is sufficient bypass volume. Any increase in infiltration volume is offset by a decrease in bypass volume. When the treatment capacity, footprint, and infiltration rates are fixed, longer drawdown times decrease the treatment flow rate as less volume can discharge through the treatment aperture and more volume is allocated as bypass (Fig. 3C). Both of these flow components exhibited significant responses, while the infiltrated volumes were constant (due to the fixed infiltration rate).

4.2. Conditional validation

Comparisons of average annual runoff calculated from TELR generally showed good correspondence with the study catchments. The results are listed in Table 7 and plotted in Fig. 6. There was little evidence of systematic bias in the TELR estimates towards universal under or over prediction (PBIAS = 5%) nor was there correspondence between relative error magnitude and catchment size. The 2 largest basins (Osgood and Eloise) that include substantial upland forested areas in addition to their urban runoff showed relative errors below 15%. The largest difference between the measured and modeled flows was in the Rocky Point catchment with a 38% underestimation by TELR. Across all 6 catchments, the APBIAS was 14%. We speculate that the large runoff discrepancy in Rocky Point may have been at least partially due to the addition of snow plowed into the dry basin from the adjacent highway, as was observed by the authors on multiple occasions. The regional NSE score was 0.97, but this value depended strongly on the relatively high annual flows from Eloise Basin. Without Eloise, the calculated NSE score is 0.88, which still represents very good performance given common interpretations of the NSE in hydrologic model assessment (Fry et al., 2013).

Results of the TELR BMP performance estimates compared to measured data are shown in Fig. 7 with measured and modeled outflow volumes for five 24-hr rainfall events between 2009 and 2011 that registered flow in at least 1 of the basins. TELR generally identified the dominant outflow components and simulated the true proportionality between outflow components for each of the test basins. For example, in the Osgood basin the bypassed volume for the October 13, 2009 event and the treated volume for the August 24, 2011 event were both within 4% of the measured values. In the cases where nearly all of the delivered water was infiltrated (Park Ave, October 13, 2009 and Rocky Point October 19, 2009) the infiltrated volumes were within 1% of measured volumes. The largest differences in the relative outflow volume allocations occurred for the Rocky Point dry basin. TELR overestimated infiltration volume at the expense of treated volume for the October 8, 2009 event by approximately 34%, but underestimated infiltration volume in place of treated volume for the June 28, 2011 event by 16%. Non-dominant flow components generally showed larger relative errors than the dominant flow components for each event, but these were usually less than 20% of the total stormwater volume received (see Fig. 7).

4.3. Model comparisons

For a suite of hydrologic and catchment conditions, TELR and the SWMM-based continuous simulation models showed good overall correspondence for hypothetical catchments with a range of soil groups, percent imperviousness, and regional precipitation zones. The results plotted in Fig. 8 show that TELR usually produced more runoff in the lower runoff catchments and less runoff in the higher runoff catchments. On average, TELR estimated 3% less runoff than NSWC (R^2 = 0.96) and 4% less than PLRM (R^2 = 0.95) with the largest differences associated with very low and very high percent impervious (5% and 95%) catchments. These differences are comparable to differences between the 2 SWMM-based continuous models, where the NSWC estimated 2.3% less runoff than PLRM (results not shown).

Table 6
Metadata for NSWC precipitation stations on the California Central Coast.

Precip site name	Abbreviation	ID	Lat	Lon	Start date	End date
			ddmm	ddmmm	YYYY/MM/DD	YYYY/MM/DD
Pinnacles Natl Monument	PINN	46926	3629	12111	1970/01/07	2006/12/27
Santa Barbara Muni Airport	SBAP	47905	3426	11950	1970/01/09	2006/12/27
Watsonville Waterworks	WTWKS	49473	3656	12146	1970/01/07	2006/12/26

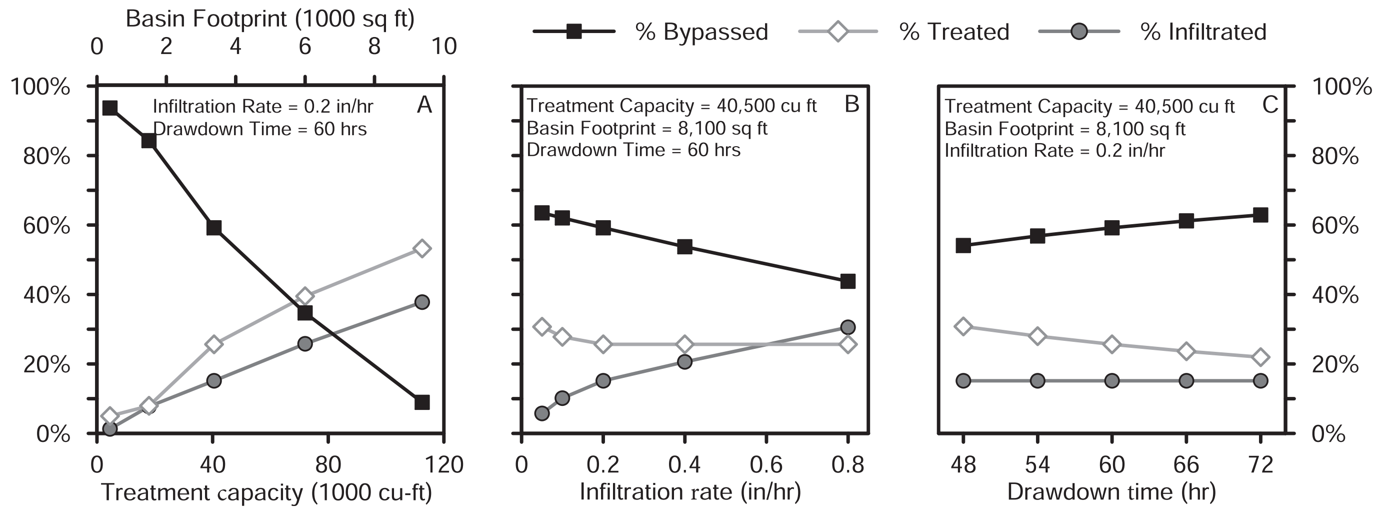

Fig. 5. Results from TELR sensitivity tests for modeling a dry basin. Estimated infiltrated, treated, and bypassed volumes for various BMP sizes (A), infiltration rates (B), and brimful drawdown times (C).

Table 7
Catchment validation results table.

Catchment	Observed flow (m^3/yr)	Modeled flow (m^3/yr)	Relative error (%)	Regional performance metrics		
				PBIAS (%)	APBIAS (%)	NSE
Osgood	66,916	76,384	−14			
Park Avenue	38,916	45,851	−18			
Rocky Point	28,863	18,037	38	−5	14	0.97
Pasadena	9305	7833	16			
Incline	15,393	13,824	10			
Eloise	2010	180,606	10			

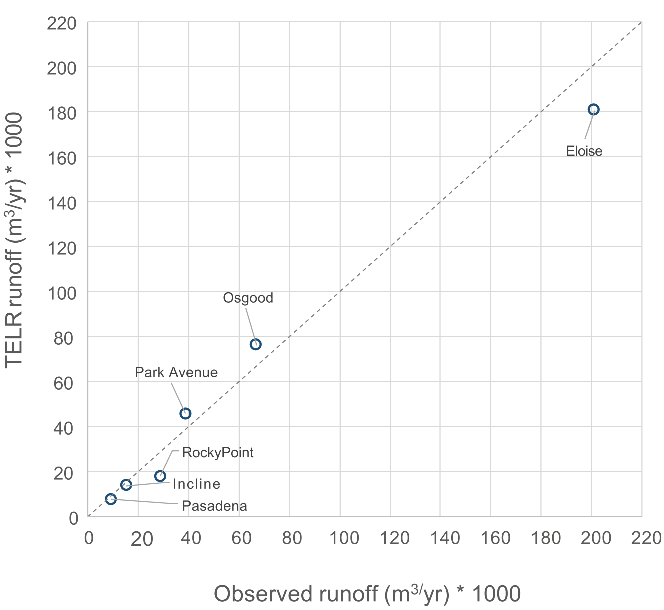

Fig. 6. Comparison of TELR modeled runoff to observed data for 6 catchments in the Lake Tahoe Region, California.

5. Discussion

Consistent with the suggestions provided by Beven and Young (2013), we have described the work presented here as *conditional validation* experiments of the TELR model approach given that only 6 study catchments in a single region of California were used, with a maximum of 2 years of data. The flashy runoff response in small urbanized catchments requires continuous hydrologic monitoring with samples at very short intervals (<1 minute) to fully capture most stormwater runoff events. This type of stormwater monitoring data are rarely collected at the same location for more than a few years. A more robust validation would include longer periods and more study catchments (e.g. Mathevet et al., 2006), but as Beven and Young (2013) point out, a model that has yet to be falsified against observational data can be considered conditionally valid and have immediate practical use pending further research.

Numeric thresholds for determining performance adequacy are not very meaningful outside the context of the model use or a benchmark for comparison (Schaefli and Gupta, 2007). One such benchmark for urban catchments is a simple empirical model such as that used by Brezonik and Stadelmann (2002) who often found good performance for urban catchments in Minnesota, USA (best $R^2 = 0.78$). While this provides some context for the performance of the TELR outputs, it should also be considered that models calibrated via regression coefficients are likely to be less reliable outside the range of data used for model fitting.

Models in general should be specified in a manner proportional to the data available to support their testing, so that practitioners do not employ tools that are fortified against falsification via excessive degrees of freedom. This would suggest that simple models are more appropriate than more complex alternatives for widespread use to quantify stormwater runoff from urban catchments, particularly when resources are limited and one primary use of the outputs is to track changes over time (e.g. Schueler, 1987;

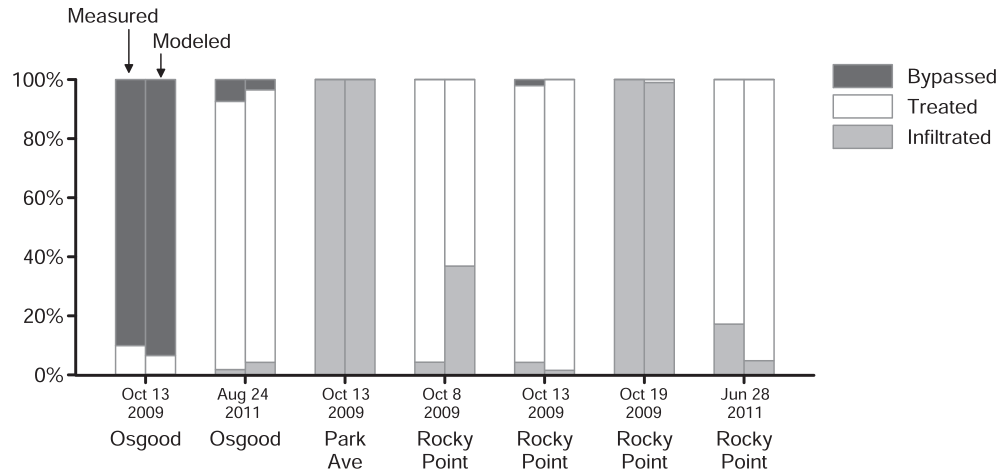

Fig. 7. Comparison between modeled and measured data for infiltration, treatment, and bypass volumes for seven 24-hr precipitation events sin South Lake Tahoe, California.

Chandler, 1993, 1994). Indeed, it was recognized long ago by the earliest developers of continuous simulation stormwater models that they would be too detailed for many users and that there is a need for a wide range of procedures for assessment of stormwater pollution control costs and priorities (Heaney et al., 1976). While process-based continuous simulation models provide a better way to understand short-term dynamics of runoff generation and timing within urban catchments and the ability to tune model parameters to more closely match observations, simpler computational approaches such as TELR may be a better alternative for stormwater managers due to lower costs and less burdensome data requirements.

While the simplified process representation employed in TELR will avoid some uncertainty via parameterization, it is more susceptible to producing less accurate runoff estimates due to the model structure including too little detail. For example, by representing infiltration using a static curve number rather than dynamically, the effects of changes to soil moisture or hydraulic conductivity that result from preceding rainstorms are not captured explicitly and would likely result in unacceptable simulation performance at daily or monthly time steps. We would expect such issues would be more pronounced in catchments with substantial natural cover. Comparable estimates to both the observed data and the SWMM-based models help to confirm that such process representation is less important when modeling annual flows for urbanized catchments. Additionally, the simpler runoff generation approach and rainfall inputs used in TELR make it easier to consistently quantify the effects of management actions over time, since rainfall inputs are the same for each year and runoff estimates are not tied to a specific calibration period or subjective parameter adjustment settings made by users.

TELR is best suited as a planning and progress tracking tool for stormwater managers in catchments with a high degree of impervious cover, where runoff travel times are short, losses via evaporation are minimal, and explicit accounting of sub-surface return flow versus groundwater losses are not required. With these limitations clearly defined, the computational simplicity of TELR has allowed migration from a spreadsheet application to a web-based platform that allows multi-catchment modeling and heuristic planning scenarios to facilitate use and further testing by municipal stormwater managers in California (www.swtelr.com). Functionality is focused on user creation of urban catchment-based maps that show spatial patterns of runoff and reductions from implemented or planned BMPs and graphs that summarize runoff impacts and reductions by land-use and receiving waters. Guidance is provided with standardized processes for creating input data and running simulations to improve consistency across users with varying levels of modeling expertise. Planned improvements include inclusion of both centralized structural BMPs (as presented herein) and decentralized BMPs that are often implemented via low impact development (LID) projects to promote diffuse infiltration or treatment of stormwater. Regional and state regulatory representatives have been key stakeholders in the development process to ensure that the input data and associated TELR outputs can be used by municipalities to comply with a number of annual MS4 permit reporting requirements.

6. Conclusions

We have described a simple approach to estimate stormwater runoff reductions from BMP implementation for tracking and reporting along with a limited performance validation. The rainfall metrics used as inputs were shown to adequately represent central tendency of the measured rainfall distribution with a calculated average annual 24-hr event mean within 3% of that of the observed data. TELR runoff estimates aligned well with measured annual runoff for the 6 study catchments measured over 2 year periods relative to a suite of regional performance metrics. TELR runoff estimates are comparable to SWMM-based models in terms of average annual runoff across urban catchments with a range of characteristics, with all results within 5% of one another. Each of the structural BMP flow components showed sensitivity to changes in the BMP specification inputs and comparison with 3 centralized structural BMPs indicated that TELR correctly categorized infiltration, treatment, and bypass volumes for a representative range of hydrologic conditions.

Given the adequacy of the performance results so far, TELR has good potential to fill the need for a practical tool to transparently identify urban catchments where the greatest stormwater runoff reduction opportunities exist and communicate the hydrologic value of stormwater investments to management, funders, regulators and the public. With a design directly targeted to the needs of stormwater practitioners and commensurate with the data commonly available to them, TELR may provide a practical alternative to track stormwater mitigation effectiveness over time as the number of cities required to do so across the US grows.

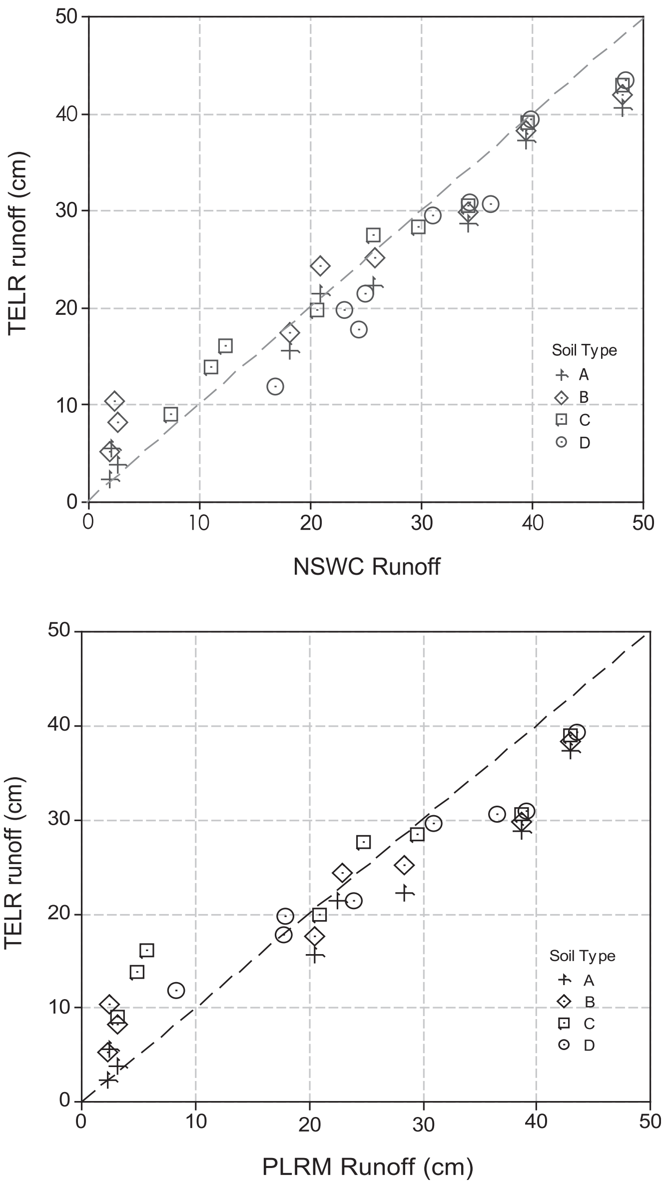

Fig. 8. Comparison between TELR runoff estimates and the SWMM-based models NSWC and PLRM for a range of catchment sizes with different soil types. Estimates are normalized by catchment area.

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