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Improved methods to estimate the effective impervious area in urban catchments using rainfall-runoff data

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SUMMARY

Impervious surfaces are useful indicators of the urbanization impacts on water resources. Effective impervious area (EIA), which is the portion of total impervious area (TIA) that is hydraulically connected to the drainage system, is a better catchment parameter in the determination of actual urban runoff. Development of reliable methods for quantifying EIA rather than TIA is currently one of the knowledge gaps in the rainfall-runoff modeling context. The objective of this study is to improve the rainfall-runoff data analysis method for estimating EIA fraction in urban catchments by eliminating the subjective part of the existing method and by reducing the uncertainty of EIA estimates. First, the theoretical framework is generalized using a general linear least square model and using a general criterion for categorizing runoff events. Issues with the existing method that reduce the precision of the EIA fraction estimates are then identified and discussed. Two improved methods, based on ordinary least square (OLS) and weighted least square (WLS) estimates, are proposed to address these issues. The proposed weighted least squares method is then applied to eleven urban catchments in Europe, Canada, and Australia. The results are compared to map measured directly connected impervious area (DCIA) and are shown to be consistent with DCIA values. In addition, both of the improved methods are applied to nine urban catchments in Minnesota, USA. Both methods were successful in removing the subjective component inherent in the analysis of rainfall-runoff data of the current method. The WLS method is more robust than the OLS method and generates results that are different and more precise than the OLS method in the presence of heteroscedastic residuals in our rainfall-runoff data.

1. Introduction

Impervious surfaces are widely used as an indicator for assessing the urbanization impacts on water resources. The increase in impervious surfaces due to urban development can affect the characteristics of a watershed, including hydrology (altering runoff volume, peak discharge rate, and baseflow), physiography (changing the morphology and temperature of streams), water quality (increasing pollutant loads), and biology (decreasing the biodiversity of streams) (Chabaeva et al., 2009). Traditionally, "total impervious area" (TIA) has been used in environmental and water resources studies as an integrative indicator of urban development and its impact on urban ecosystem; however, recent studies conclude that the "effective impervious area" (EIA), or the portion of TIA that is hydraulically connected to the drainage system is a better indicator of runoff in urbanized areas (Booth and Jackson, 1997). Hydraulic connectedness occurs where runoff from the impervious area travels over paved surfaces, drain pipes, or other conveyance and detention structures that do not reduce runoff volume before discharging into a stormwater drainage system inlet (EPA, 2014). Another parameter related to impervious area is directly connected impervious area (DCIA). These areas are directly connected to the drainage system by impervious pathways and can be defined by field inspection or accurate map data. In contrast to DCIA, EIA is dependent on rainfall and runoff response and cannot be defined solely by field inspection or map data.

TIA is often used to determine runoff hydrograph and design stormwater control measures (SCMs) in catchments. However, EIA is the most important parameter in determining urban runoff volumes (Janke et al., 2011). The incorrect use of TIA instead of EIA in rainfall-runoff modeling causes runoff volumes and rates to be overestimated (Alley and Veenhuis, 1983; Ravagnani et al., 2009). In addition, EIA is of utmost importance in terms of water

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quality as most of the small (frequent) storms contribute to runoff through EIA (Lee and Heaney, 2003). Thus, EIA is a better variable than TIA for predicting pollutant concentrations and loads in predictive models for urbanized areas (Hatt et al., 2004).

Urban storm sewer networks are inherently complex (Ebrahimian et al., 2015). To decrease the discharge into these networks and improve the water quality in receiving waters, SCMs are being employed. Many of SCMs, such as bio-infiltration cells, infiltration basins, and permeable pavements, reduce EIA by decreasing the hydraulic connection of impervious surfaces to storm sewer systems (Asleson et al., 2009; Olson et al., 2013; Paus et al., 2014; Ahmed et al., 2015). Development of reliable tools for quantifying EIA is a substantial knowledge gap in these efforts (Fletcher et al., 2013).

1.1. Background

The primary means of EIA determination is by calibrating hydrologic models where EIA can be fitted to the measured runoff hydrograph. However, in cases where runoff from pervious area is a substantial portion of the total runoff, results are also dependent on the calibration of infiltration parameters and large errors may occur (Alley and Veenhuis, 1983). Thus, direct determination of EIA will allow infiltration parameters to be more accurately estimated. The existing methods for the direct determination of EIA include statistical analysis of rainfall and runoff data (Boyd et al., 1993, 1994) and GIS techniques by the use of elevation and land cover spatial data (Han and Burian, 2009). Empirical relations from regression analysis based on the results of model calibration in some urban areas in Oregon, USA have also been developed for EIA determination by Laenen (1983) and Sutherland (1995). However, these relations may not produce accurate results in all areas (Laenen, 1983). Other existing methods actually determine DCIA rather than EIA. Field investigations along with aerial photo interpretation and GIS data compilation (Lee and Heaney, 2003; Bochis and Pitt, 2005; Roy and Shuster, 2009) are methods that can determine DCIA but are time consuming, labor intensive and costly for larger catchments. Empirical relations have also been developed from regression analysis based on the results of field surveys for predicting DCIA (e.g., Alley and Veenhuis, 1983) which have been found to be ineffective at estimating observed DCIA in terms of TIA (Roy and Shuster, 2009).

Several studies have been performed to assess and compare different techniques for estimating TIA (Roso et al., 2006; Chabaeva et al., 2009; Beighley et al., 2009) and to study the role of imperviousness and its spatial distribution in the hydrology of urban catchments (Mejía and Moglen, 2009, 2010a,2010b). However, little work has been conducted with regard to the direct and accurate determination of EIA. The existing GIS method (Han and Burian, 2009) needs several GIS data inputs and also has to be completed with field surveys that make it expensive and time consuming. Since the determination of EIA inherently requires the assessment of losses along the flow paths of impervious runoff, the analysis of rainfall-runoff data for different storm events (Boyd et al., 1993) is the best approach among current EIA assessment methods. Rainfall-runoff derived EIA estimates are necessary to evaluate the accuracy of these other methods. However, there are issues with the analysis of rainfall-runoff data. Further research is needed to fill the knowledge gap in improving the EIA estimation methods based on rainfall-runoff data (Fletcher et al., 2013; Ebrahimian, 2015a).

1.2. Objective

The current method for evaluating EIA using only rainfall-runoff data is the method of Boyd et al. (1993) (Boyd's method). Improving the use of the Boyd's method by a careful examination of its theoretical framework is the main objective of this study. To fulfil our objective, first, the theory behind the original Boyd's method is generalized using the general linear least square model and a general criterion for categorizing runoff events. Issues related to the precision of the EIA estimates are then identified and discussed. We evaluate two improved methods based on ordinary and weighted least squares (OLS and WLS) techniques using a new criterion for categorizing runoff events. The weighted least squares (WLS) method is then applied to eleven urban catchments in Europe, Canada, and Australia that were previously used in Boyd et al. (1993) and the EIA results are compared to map measured DCIA values. Both methods are also applied to nine urban catchments in Twin Cities, Minnesota, USA and precision of the results in each method is assessed. The results are discussed and conclusions are provided on using the improved methods for determining EIA in gauged urban catchments.

2. Theory

Following the analysis of Boyd et al. (1993, 1994), the EIA fraction (f_{EIA}) in an urban catchment (the ratio of EIA over total catchment area), can be determined by the use of datasets composed of pairs of rainfall depth and runoff depth. For a catchment divided into either EIA or non-EIA areas, the runoff volume is simply defined as:

$$V_t = Q_{\text{EIA}}A_{\text{EIA}} + Q_r(A_t - A_{\text{EIA}}) \tag{1}$$

where V_t = total runoff volume, Q_{EIA} = runoff depth for effective impervious area, which is equal to the rainfall depth (P) minus the initial abstraction of impervious area (I_a), A_{EIA} = area of the effective impervious surfaces, Q_r = runoff depth for the rest of catchment and is generally a complex function of P, and A_t = total drainage area of catchment. By dividing Eq. (1) by A_t the total runoff depth (Q_t) is defined as:

$$Q_t = (P - I_a)f_{\text{EIA}} + Q_r(1 - f_{\text{EIA}}) \tag{2}$$

where observed data are available with our methods to compute P and Q_t. Eq. (2) is valid for $P > I_a$. For small storms where runoff is only from the impervious area (i.e., $Q_r = 0$), Eq. (2) becomes:

$$Q_t = (P - I_a)f_{\text{EIA}} \tag{3}$$

As indicated by Eq. (2), the relationship between runoff depth and rainfall is likely complex using all storms in the dataset. However, Eq. (3) shows that, runoff depth varies linearly with rainfall depth if the events are chosen to include runoff only from impervious area. The slope of this line is the EIA fraction (f_{EIA}). Events for this plot are called EIA events. Eq. (3) also shows that the x-intercept of the line can be used to determine the initial abstraction of the impervious area (I_a) for a known f_{EIA}. For larger storms, pervious area and non-effective impervious area can also contribute to runoff. The storm events that generate runoff from both pervious and impervious surfaces are called combined events. The data points associated with combined events would lie above the line given by Eq. (3). Fig. 1 illustrates an example of EIA and combined events in an urban catchment in St. Paul, Minnesota, USA.

Linear regression models can be used to determine the EIA fraction and I_a from observed runoff and rainfall depths. The linear statistical model in matrix form can be written as:

$$\mathbf{y} = \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

where $\mathbf{y}$ is a $(n \times 1)$ vector of runoff depths (dependent variable), n = total number of events, $\mathbf{x}$ is a $(n \times 2)$ matrix where the elements in the first column are ones and in the second column are rainfall depths (independent variable), and $\boldsymbol{\beta}$ is a (2×1) vector of

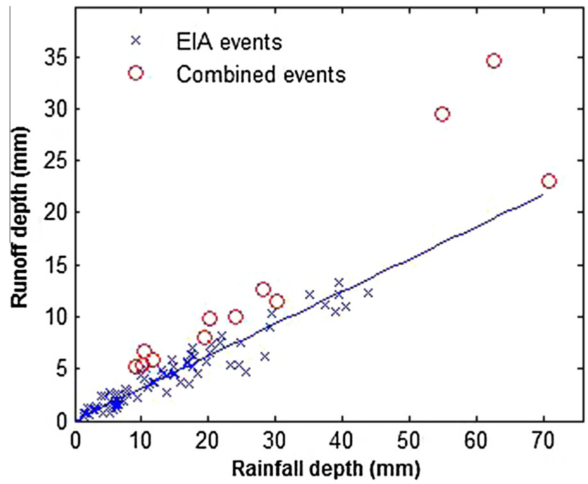

Fig. 1. Example of EIA and combined events in Phalen Creek catchment, Minnesota.

population parameters where β_0 and β_1 correspond to $-I_a f_{EIA}$ and f_{EIA}, respectively, and $\boldsymbol{\varepsilon}$ is a $(n \times 1)$ vector of residuals.

In order to determine the EIA fraction, we need to separate storms into either EIA or combined events. We define an EIA criterion (δ_c) for this categorization as:

$$y_j = \begin{cases} EIA\ event & \text{if } \varepsilon_j \leqslant \delta_c \\ Combined\ event & \text{if } \varepsilon_j > \delta_c \end{cases} (j = 1, \ldots, n) \tag{5}$$

where y_j is the jth event in the runoff depth vector, ε_j is the random error for the jth event, and δ_c is the EIA criterion.

2.1. Generalized Least Squares (GLS) method

In the general linear model (Eq. (4)), the variance–covariance matrix of residuals ($E[\boldsymbol{\varepsilon\varepsilon}^{\mathbf{T}}]$) is defined as (Beck and Arnold, 1977):

$$E[\boldsymbol{\varepsilon\varepsilon}^{\mathbf{T}}] = \begin{bmatrix} VAR(\varepsilon_1) & \cdots & COV(\varepsilon_1, \varepsilon_n) \\ \vdots & \ddots & \vdots \\ COV(\varepsilon_n, \varepsilon_1) & \cdots & VAR(\varepsilon_n) \end{bmatrix} \tag{6}$$

where $E[]$ indicates the expected value of the terms in brackets, superscript $\mathbf{T}$ denotes the transpose of a matrix, $VAR(\varepsilon_j)$ is the variance of ε_j and $COV(\varepsilon_i,\varepsilon_j)$ is the covariance of ε_i and ε_j. For uncorrelated and homoscedastic (equal variance) residuals, the variance–covariance matrix can be simplified as $E[\boldsymbol{\varepsilon\varepsilon}^{\mathbf{T}}] = \sigma^2\mathbf{I}$, where $\mathbf{I}$ denotes the identity matrix and σ^2 = constant variance of residuals. By using $E[\boldsymbol{\varepsilon\varepsilon}^{\mathbf{T}}] = \sigma^2\boldsymbol{\Psi}$, where $\boldsymbol{\Psi}$ is an $(n \times n)$ positive definite symmetric matrix and σ^2 is a normalizing scalar (equal to the variance of residuals if they were constant and uncorrelated with other observations), and if $E[\boldsymbol{\varepsilon\varepsilon}^{\mathbf{T}}]$ is known, the general statistical model (Eq. (4)) can be transformed by multiplying an $(n \times n)$ matrix $\mathbf{Z}$ so that $\mathbf{Z\Psi Z^T} = \mathbf{I}$. A matrix $\mathbf{Z}$ with such property always exists (Judge et al., 1988). Hence, the transformed statistical model is found as:

$$\mathbf{y}^* = \mathbf{x}^*\boldsymbol{\beta} + \boldsymbol{\varepsilon}^* \tag{7}$$

where $\mathbf{y}^* = \mathbf{Zy}$, $\mathbf{x}^* = \mathbf{Zx}$, and $\boldsymbol{\varepsilon}^* = \mathbf{Z}\boldsymbol{\varepsilon}$.

It can be shown that $E[\boldsymbol{\varepsilon}^*\boldsymbol{\varepsilon}^{*\mathbf{T}}] = \sigma^2\mathbf{I}$ and the best linear unbiased estimator of $\boldsymbol{\beta}$ is the generalized least squares estimator ($\mathbf{b_{gls}}$). Mathematically, the generalized least squares estimators are (Judge et al., 1988):

$$\mathbf{b_{gls}} = (\mathbf{x^T}\boldsymbol{\Psi}^{-1}\mathbf{x})^{-1}\mathbf{x^T}\boldsymbol{\Psi}^{-1}\mathbf{y} \tag{8}$$

The variance–covariance matrix of $\mathbf{b_{gls}}$ (i.e., $\mathbf{s}^2(\mathbf{b_{gls}})$) is defined as (Judge et al., 1988):

$$\mathbf{s}^2(\mathbf{b_{gls}}) = \sigma^2(\mathbf{x^T}\boldsymbol{\Psi}^{-1}\mathbf{x})^{-1} \tag{9}$$

The generalized least squares (GLS) method provides a general theoretical framework for representing the variance and covariance structure of the residuals. For our application, diagonal elements of $\boldsymbol{\Psi}$ are the normalized (by σ^2) variances of residuals corresponding to each of the observed rainfall depths. The off-diagonal elements are the normalized covariance of residuals among the different observed rainfall depths. For example, the jth column of the ith row of $\boldsymbol{\Psi}$ corresponds to the normalized covariance of the residuals corresponding to the ith and jth rainfall depths. Despite the general form of GLS method, $\boldsymbol{\Psi}$ is generally unknown and unobservable in hydrological applications (Stedinger and Tasker, 1985; Pandey and Nguyen, 1999). Hence an estimator of $\boldsymbol{\Psi}$ must be used, which leads to the estimated generalized least squares estimator (Stedinger and Tasker, 1985; Judge et al., 1988). Two common estimates of $\boldsymbol{\Psi}$ are ordinary least squares (OLS) and weighted least squares (WLS) that will be discussed below.

2.2. Ordinary Least Squares (OLS) method

The ordinary least squares (OLS) method minimizes the sum of squared residuals (SSE) between observations y_j ($j = 1, \ldots, n$) and their regression values. As discussed by Beck and Arnold (1977), the statistical assumptions inherent in the OLS method are: (1) no measurement errors in the independent variable, (2) mean residual of zero ($E(\varepsilon_j) = 0$); (3) normal distribution of residuals (ε_j's); (4) homoscedastic residuals and (5) uncorrelated residuals. The consequence is not severe if the assumptions 1, 2, and 3 are violated. However, violations of assumptions 4 and 5 cause the uncertainty of estimated parameters to increase (Beck and Arnold, 1977). When the above assumptions are met, the OLS method provides unbiased estimators that have minimum variance (Stuart et al., 2004).

For homoscedastic and uncorrelated residuals, the variance–covariance matrix of residuals of Eq. (6) is simplified as $E[\boldsymbol{\varepsilon\varepsilon}^{\mathbf{T}}] = \sigma^2\mathbf{I}$ where σ^2 = constant variance of residuals (ε_j's) and $\mathbf{I}$ = Identity matrix. Hence, by using $\boldsymbol{\Psi} = \mathbf{I}$, Eqs. (8) and (9) are written as Eqs. (10) and (11), respectively.

$$\mathbf{b_{ols}} = (\mathbf{x^Tx})^{-1}\mathbf{x^Ty} \tag{10}$$

$$\mathbf{s}^2(\mathbf{b_{ols}}) = \mathrm{MSE}(\mathbf{x^Tx})^{-1} \tag{11}$$

where subscript **ols** denotes the ordinary least squares estimator and MSE is the unbiased estimator of σ^2 which is defined as

$$\mathrm{MSE} = \frac{(\mathbf{y} - \mathbf{xb_{ols}})^{\mathbf{T}}(\mathbf{y} - \mathbf{xb_{ols}})}{n-2} \tag{12}$$

For the problem where runoff depth is the dependent variable ($\mathbf{y}$) and rainfall depth is the only independent variable ($\mathbf{x}$) and given the above mentioned statistical assumptions, the OLS regression will results in the parameters ($\mathbf{b_{ols}}$) to be simply obtained from:

$$y_j = b_1 x_j + b_0 \tag{13}$$

where Eq. (13) is similar to Eq. (3) and b_0 and b_1 are the elements of $\mathbf{b_{ols}}$ which correspond to $-I_a f_{EIA}$ and f_{EIA}, respectively.

Estimates of f_{EIA} using the OLS method are appropriate and statistically efficient when the flow measurements are "equally reliable" (Tasker and Stedinger, 1989).

2.3. Weighted Least Squares (WLS) method

Violation of the homoscedastic condition (i.e., heteroscedasticity) is often caused by the decreased accuracy of the runoff measurements with an increase in precipitation. Although natural variability in antecedent conditions and other factors can also cause heteroscedasticity, these factors are likely small for runoff from impervious surfaces. For the general linear statistical model (Eq. (4)) with $E[\boldsymbol{\varepsilon}] = 0$, heteroscedasticity exists if the variance of residuals is not constant (Judge et al., 1988). To account for heteroscedastic residuals, the WLS technique is used to estimate regression parameters of b_0 and b_1. WLS is based on a variance–covariance matrix of uncorrelated residuals defined as (Beck and Arnold, 1977):

$$E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathbf{T}}] = \begin{bmatrix} VAR(\varepsilon_1) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & VAR(\varepsilon_n) \end{bmatrix} \tag{14}$$

or by assuming $E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\mathbf{T}}] = \sigma^2\boldsymbol{\Psi}$,

$$\boldsymbol{\Psi} = \begin{bmatrix} 1/w_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/w_n \end{bmatrix} \tag{15}$$

where $\boldsymbol{\Psi}$ is a diagonal matrix in which the diagonal elements are $1/w_j$, $(j = 1, \ldots, n)$ and σ^2 is the normalizing scalar. Here, the residuals are uncorrelated but have different variances and w_j is the weight of observation j $(j = 1, \ldots, n)$. Conceptually, runoff depth observations with large residual variances are less reliable and therefore WLS method assigns them a smaller "weight". Mathematically, the dimensionless weight is defined for each observation as w_j

$$w_j = \frac{\sigma^2}{VAR(\varepsilon_j)} \quad (j = 1, \ldots, n) \tag{16}$$

Similar to the OLS technique, a sum of squared residuals is minimized in WLS. For the WLS method, this sum is defined as (Beck and Arnold, 1977):

$$\mathrm{SSE} = \sum_{j=1}^{n} w_j e_j^2 \tag{17}$$

where e_j is the sample estimate of ε_j. The WLS estimator of $\boldsymbol{\beta}$ (i.e., $\mathbf{b_{wls}}$) is (Beck and Arnold, 1977):

$$\mathbf{b_{wls}} = (\mathbf{x^T}\boldsymbol{\Psi}^{-1}\mathbf{x})^{-1}\mathbf{x^T}\boldsymbol{\Psi}^{-1}\mathbf{y} \tag{18}$$

where $\boldsymbol{\Psi}^{-1}$ (inverse of $\boldsymbol{\Psi}$) is a diagonal matrix where its diagonal elements are w_j, $(j = 1, \ldots, n)$. Hence, the OLS method is a special case of WLS method with equal weights.

The variance–covariance matrix of residuals can be estimated using the multiplicative heteroscedasticity method given by Judge et al. (1988) where $VAR(\varepsilon_j)$ is assumed to be an exponential function of the independent variable and σ^2 is considered as an average of $VAR(\varepsilon_j)$ estimates. The unknown weights are then estimated based on the obtained variance using Eq. (16). Finally, $\boldsymbol{\Psi}$ is composed as a diagonal matrix with diagonal elements as $\frac{1}{w_j}(j = 1, \ldots, n)$, and the inverse of $\boldsymbol{\Psi}$ will be used in Eq. (18) to estimate I_a and f_{EIA}.

The uncertainty in WLS estimators can be assessed using the variance–covariance matrix of $\mathbf{b_{wls}}$ (i.e., $\mathbf{s}^2(\mathbf{b_{wls}})$) which is defined as:

$$\mathbf{s}^2(\mathbf{b_{wls}}) = \mathrm{MSE}'(\mathbf{x^T}\boldsymbol{\Psi}^{-1}\mathbf{x})^{-1} \tag{19}$$

where MSE′ is an unbiased estimator of σ^2 (Judge et al., 1988):

$$\mathrm{MSE}' = \frac{\mathbf{e^T}\boldsymbol{\Psi}^{-1}\mathbf{e}}{n-2} \tag{20}$$

where $\mathbf{e}$ is defined as $\mathbf{e} = \mathbf{y} - \mathbf{x}\mathbf{b_{wls}}$.

2.4. EIA criterion

Selection of an appropriate EIA criterion (δ_c in Eq. (5)) is necessary to achieve an appropriate categorization of data into either EIA events or combined events. In the study of Boyd et al. (1993, 1994) a constant EIA criterion equal to 1 mm was used (i.e., δ_c = 1 mm). By considering smaller values for δ_c (e.g., 0.5 mm) the standard error (SE) of the regression line for EIA will decrease; but, the variance of f_{EIA} (as a measure of the uncertainty of slope parameter) will generally increase. An examination of various δ_c criteria between 0.5 and 2.5 mm indicated that δ_c = 1 mm is an appropriate choice. However, a constant δ_c corresponds to the ideal case where the runoff measurement errors are negligible. For other cases, the scatter of data points around the regression line may be associated with two items: (1) contributing surfaces other than EIA in runoff generation (i.e., effect of combined events), and (2) runoff measurement errors. Uncertainty in runoff measurements results in a larger standard error of regression. To address both items, a new EIA criterion is defined using the maximum of the existing constant 1-mm depth and a depth corresponding to two standard errors of regression. This latter depth is simple to determine and resulted in reasonable f_{EIA} estimates compared with their corresponding land use and f_{TIA} (Ebrahimian, 2015b). The new EIA criterion is defined as:

$$\delta_c = \max[2\ \mathrm{SE}, 1\ \mathrm{mm}] \tag{21}$$

In Eq. (21), max [ ] is the maximum of the terms in brackets and SE is the standard error of regression and is defined as $\mathrm{SE} = \sqrt{\mathrm{MSE}}$, where MSE is residual mean square or the average squared deviations about the regression line. The outcome of using this new EIA criterion will be presented and discussed in Section 5. It should be noted that the standard error in WLS (i.e., $\mathrm{SE_{WLS}}$) is based on the transformed variables ($\mathbf{x}^*$ and $\mathbf{y}^*$ in Eq. (7)) in the WLS method and is different than the SE in OLS. The standard error of the predicted values by the WLS method is often smaller than that of the OLS method (Tasker, 1980; Stedinger and Tasker, 1985). Following Willett and Singer (1988), a "pseudo $\mathrm{SE_{WLS}}$" given by Eq. (22) is used for SE in Eq. (21) for the WLS method to make representative comparisons with SE in the OLS method.

$$\text{Pseudo } \mathrm{SE_{WLS}} = \sqrt{\frac{(\mathbf{y} - \mathbf{x}\mathbf{b_{wls}})^{\mathbf{T}}(\mathbf{y} - \mathbf{x}\mathbf{b_{wls}})}{n-2}} \tag{22}$$

3. Successive least square methods for determining EIA

Boyd's method uses several regressions before selecting the final regression parameters of $b_1 = f_{\mathrm{EIA}}$ and $b_0 = -I_a f_{\mathrm{EIA}}$. With their method, runoff depths are first plotted against rainfall depth for different storms in the catchment dataset and data that are more than 1 mm above the regression line are omitted. A new line is then fitted to the remaining data to re-evaluate the data and identify the other points that might still include pervious runoff (i.e., runoff from pervious area). A constant EIA criterion of δ_c = 1 mm was used by Boyd et al. (1993, 1994). Since the events with smaller rainfall depths are likely to include EIA events only, Boyd's method analyzes these events separately to obtain the "most consistent" EIA fraction. The method, therefore, relies on professional judgment in selecting the smaller events and has an inherent subjective component. To remove subjectivity in the analysis, we introduced a new EIA criterion in the previous section (i.e., Eq. (21)) into the theoretical framework. This criterion is proposed to be used in a successive least square regression process for determining EIA fraction based on rainfall-runoff data. Two specific cases of this successive process based on OLS and WLS techniques are introduced below.

3.1. Successive ordinary least squares method for determining EIA

The following steps are used to determine EIA fraction using successive OLS regressions with the general EIA criterion of Eq. (21):

1. Plot runoff depth against rainfall depth for measurements from the catchment of study.
2. Fit a straight line to the measured data using OLS regression.
3. Omit the points that are greater than the EIA criterion (δ_c in Eq. (21)) above the regression line and fit a new line using OLS to the remaining data points.
4. If the distance of all the points above the line is less than "δ_c", the slope of the line equals f_{EIA}; otherwise, step 3 is repeated until all the points above the line lie within "δ_c" of the line.

Runoff measurement errors cause scatter in the dataset which might result in a small negative value for the x-intercept of the fitted line at the final step of the method. In such cases, the regression line is forced to go through the origin (i.e., $I_a = 0$). Then step 4 will be repeated using the zero intercept.

Since this method is based on successive regressions and the OLS method is utilized, the method is called "Successive Ordinary Least Squares" or "successive OLS" herein. The successive OLS method with an EIA criterion as Eq. (21) can be used where the runoff measurement errors are uncorrelated with other observations and have equal variances.

3.2. Successive weighted least squares method for determining EIA

For heteroscedastic residuals, the regression parameters obtained from OLS no longer correspond to the minimum variance estimators (Beck and Arnold, 1977) and hence, greater uncertainty exists in the estimates of f_{EIA} and I_a. To account for heteroscedasticity in the dataset and decrease the uncertainty of f_{EIA} estimates, the WLS method is proposed to be utilized in the abovementioned successive regression process and is called the successive WLS method. This method is recommended for datasets with uncorrelated but heteroscedastic residuals. Substituting OLS with WLS, the general framework and different steps of the successive WLS method would be similar to the successive OLS method as described in Section 3.1. The EIA criterion (δ_c) to be used in the successive WLS method is found using Eqs. (21) and (22).

4. Study sites and data

Two different datasets are used to evaluate our EIA methods. The first dataset is for eleven urban catchments in Europe, Canada, and Australia that were used by Boyd et al. (1993). A complete description of these catchments can be found in Boyd et al. (1993). All of these catchments have residential land uses except Vika (VIK) which has commercial land use. An important feature of the first dataset is that map-measured DCIA values are also available (Boyd et al., 1993).

The second dataset is for nine monitored catchments in the Capitol Region Watershed District (CRWD). This watershed is highly-urbanized located in the Upper Mississippi River basin, USA with a drainage area of 41 square-miles. Rainfall records and runoff volume data were provided by the CRWD monitoring program which undergoes an extensive quality control process by CRWD staff. All of the study sites in CRWD have residential land uses except Sarita, which includes institutional and farm land uses. Table 1 summarizes description of the study catchments including monitoring site name, location, corresponding drainage area and years of monitoring.

Traditional validation methods assess the accuracy of proposed theoretical approaches by comparing predicted values to those observed. However for our EIA methods, there are no independent "observed" values. The runoff contribution from TIA is dependent on the runoff losses between the impervious sources and storm sewers. To determine these losses, an analysis of observed rainfall and corresponding runoff data is needed. Hydrologic models can be used to provide an independent estimate of EIA; however, estimates from these models are inferior because their values are dependent on the proper representation of complex infiltration and runoff processes that include uncertain catchment parameters. DCIA is a measure of connectedness of impervious areas and can be measured from map data or field inspection. This measure is therefore independent of rainfall-runoff data. The f_{EIA} estimates from

Table 1
Description of the study catchments.

Row	Monitoring site name	Location	Drainage area (ha)	Monitoring years
Boyd et al. (1993)				
1	Luzzi (LUZ)	Luzzi, Italy	1.73	1979–1980
2	Munkerisparken (MUN)	Lingby, Denmark	6.44	1981
3	Vika (VIK)	Oslo, Norway	10.1	1974–1975
4	Clifton Grove (CLI)	Nottingham, GB	10.6	1980–1981
5	Jamison Park (JAM)	Sydney, Australia	22.1	1983–1988
6	Malvern (MAL)	Burlington, Canada	23.3	1973–1974
7	Miljakovac (MIL)	Belgrade, Yugoslavia	25.5	1984–1985
8	Maroubra (MAR)	Sydney, Australia	57.3	1977–1988
9	East York (YORK)	Toronto, Canada	155	1976–1977
10	Strathfield (STR)	Sydney, Australia	234	1977–1988
11	Livry Gargan (LIV)	Saint Denis, France	253.5	1983–1984
Capitol Region Watershed District, Minnesota				
1	Arlington-Hamline Under-Ground Facility (AHUG)	Saint Paul, MN, USA	15.9	2007–2012
2	Golf Course Pond inlet (GCP)	Saint Paul, MN, USA	51.8	2008–2012
3	Como 3	Saint Paul, MN, USA	185.8	2009–2012
4	Sarita wetland inlet (Sarita)	Saint Paul, MN, USA	376	2006, 2008–2009
5	Trout Brook-East Branch (TBEB)	Saint Paul, MN, USA	377.2	2006–2012
6	East Kittsondale (EK)	Saint Paul, MN, USA	451.6	2005–2012
7	Phalen Creek (PC)	Saint Paul, MN, USA	579.9	2005–2012
8	Saint Anthony Park (SAP)	Saint Paul, MN, USA	1007.3	2005–2012
9	Trout Brook Outlet (TBO)	Saint Paul, MN, USA	2034.8	2007–2012

our successive WLS method are compared to observed fractions of DCIA (f_{DCIA}) for our first data set. Since they are different measures of connectedness, this comparison only provides general information on the appropriateness of our approach. Differences in the inherent uncertainties in estimates provide another valuable criterion for assessing the suitability of new methods. Greater confidence can be placed on computed values that have smaller variances. Therefore, our evaluation of our methods also includes a comparison of the standard deviation of f_{EIA}. This comparison is done for both data sets.

5. Results and discussion

Residual plots were used in our study to investigate homoscedasticity and uncorrelated residuals (Troutman, 1985; Driver and Troutman, 1989). While these plots indicated uncorrelated residuals for the catchments of study, heteroscedasticity was also indicated in some cases. Fig. 2, for example, presents the standardized residual plot for the GCP catchment in Minnesota, USA. The residuals in this plot seem to be uncorrelated with other observations, but do not have a constant variance throughout the entire range of rainfall depths which is a sign of heteroscedasticity in the monitoring data of this catchment.

Runoff is also subjected to monitoring equipment errors. Hence, prior to analysis of the rainfall-runoff data, we identified the events with a standardized residual less than −2 as outliers and removed them from the data set. Also, the spatial variation of rainfall may cause the measured rainfall in a gauge not to correspond to the rainfall over the entire catchment. Thus, prior to the rainfall-runoff analysis, a modified coefficient of spatial variation (MCSV) of rainfall (Ebrahimian et al., 2016) was utilized to identify rainfall events with a high spatial variability for the nine urban catchments in Minnesota. Then, the rainfall events with high spatial variability (i.e., MCSV > 0.5) were excluded from dataset. MCSV might be interpreted as coefficient of variation of rainfall depth using multiple rain gauges modified to avoid losing large portions of low rainfall data. Details of this MCSV analysis can be found in Ebrahimian et al. (2016).

Computer codes were developed in MATLAB (MathWorks, Inc., Release 2014a) to estimate f_{EIA} and plot the categorization of EIA and combined events in the successive OLS and WLS methods from rainfall-runoff data. The successive OLS and WLS methods with the EIA criterion given in Eq. (21) were applied to the same rainfall-runoff datasets from eleven urban catchments used by Boyd et al. (1993). Table 2 presents the f_{EIA} values from the Boyd's method and both the OLS and WLS methods for those eleven catchments. A good agreement is seen between the f_{EIA} values from the Boyd's and OLS methods except for the STR and LUZ catchments where the f_{EIA} estimates are notably higher in the OLS method. This may be explained by the heteroscedasticity in the dataset of these two catchments, and was likely corrected by the application of user's judgment in Boyd's method. As the WLS method addresses the heteroscedasticity issue, it generates f_{EIA} results that are close to those in Boyd's method for the two mentioned catchments. Because of the subjective component of Boyd's method, the precise reasons for the differences in f_{EIA} results are somewhat ambiguous. Hence, the use of our method that automates the estimation of f_{EIA} and addresses the heteroscedasticity in the dataset (i.e., successive WLS method) provides a better framework for understanding differences among watersheds.

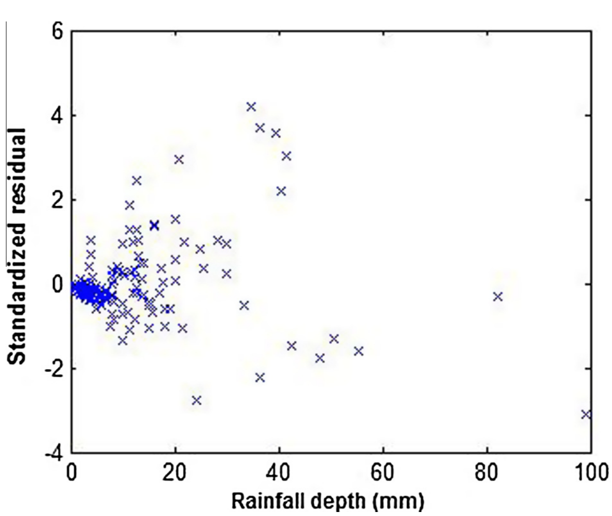

Fig. 2. Standardized residual plot for the GCP catchment in Saint Paul, Minnesota.

The f_{TIA} and f_{DCIA} (DCIA fraction) values in Table 2 are from Boyd et al. (1993) and presented herein for comparison with the f_{EIA} values. The f_{DCIA} values in Table 2 are based on map measurements. There are a number of uncertainties in these map measurements, including water retention on the impervious surface, infiltration through cracks in the impervious surface, and direct connection of downspouts to the storm sewers. As previously discussed, f_{EIA} and f_{DCIA} are a different measure of connectedness of impervious area, but still provide general information on the appropriateness of our estimate of f_{EIA}. The f_{EIA} results from the successive WLS method were plotted against the measured f_{DCIA} values and a regression line with zero intercept was fitted to the data points (Fig. 3). While for some catchments the f_{EIA} value is slightly greater than f_{DCIA}, the regression line in Fig. 3 shows that f_{EIA} is about 0.77 of f_{DCIA} in the eleven catchments of study. This agrees with conclusions from other studies (Boyd et al., 1993; Melanen and Laukkanen, 1980) which found f_{EIA} to be 0.8–0.9 of f_{DCIA} in most urban catchments.

Standard deviation of the f_{EIA} ($s(f_{EIA})$) is a measure of uncertainty of f_{EIA} estimates. Values of $s(f_{EIA})$ are presented for all the study catchments with both OLS and WLS methods in Table 2. For the WLS method, $s^2(f_{EIA})$ was calculated using Eq. (19). Because Eq. (11) is based on the assumption of homoscedasticity, the $s(f_{EIA})$ values in Table 2 for the OLS method were calculated based on Eq. (23) (Judge et al., 1988), which allows a more representative comparison with the WLS method.

$$\mathbf{s}(\mathbf{b_{ols}}) = \left[\mathrm{MSE}'(\mathbf{x^T x})^{-1}\mathbf{x^T \Psi x}(\mathbf{x^T x})^{-1}\right]^{0.5} \tag{23}$$

Both successive OLS and WLS methods with the proposed EIA criterion as Eq. (21) were also used to determine f_{EIA} for nine catchments in CRWD, Minnesota, USA. Table 3 shows the results. The TIA fractions (f_{TIA}) for these nine catchments were determined by Ebrahimian (2015b) and are also presented in Table 3. The $s(f_{EIA})$ values in Table 3, were calculated based on Eqs. (19) and (23) for the WLS and OLS methods, respectively.

To compare the f_{EIA} estimates from successive OLS and WLS methods, f_{EIA} values from the WLS method were plotted against those in the OLS method (Fig. 4) for all twenty study catchments of this study. Although f_{EIA} values from the WLS method for most of the study sites differ only slightly from that obtained with the OLS method, the WLS method has resulted in a notably smaller f_{EIA} for some sites such as STR, LUZ and MAL, in Table 2 and Sarita, Como3, and GCP in Table 3. To compare the uncertainty of the f_{EIA} estimates from OLS and WLS methods, $s(f_{EIA})$ from the WLS method were plotted against that in the OLS method for all of the twenty study catchments in Fig. 5. As seen in Fig. 5, $s(f_{EIA})$ values in all the study catchments decreased by using the WLS method.

Application of the improved methods to the twenty study catchments indicated that both the successive OLS and WLS methods can separate EIA events from combined events in each dataset.

Table 2
Measured TIA and DCIA fractions (f_{TIA} and f_{DCIA}), estimated EIA fraction (f_{EIA}) and standard deviation of the estimated EIA fractions ($s(f_{EIA})$) for the eleven catchments of Boyd et al. (1993) in Boyd, OLS and WLS methods.

Row	Catchment name	Boyd et al. (1993)			OLS		WLS	
		f_{TIA}	f_{DCIA}	f_{EIA}	f_{EIA}	$s(f_{EIA})$	f_{EIA}	$s(f_{EIA})$
1	Maroubra (MAR)	0.52	0.16	0.157	0.156	0.005	0.159	0.003
2	Strathfield (STR)	0.5	0.18	0.289	0.768	0.028	0.300	0.009
3	Jamison Park (JAM)	0.36	0.33	0.207	0.331	0.069	0.349	0.025
4	Malvern (MAL)	0.34	0.34	0.337	0.355	0.045	0.297	0.010
5	East York (YORK)	0.49	0.44	0.478	0.499	0.030	0.475	0.023
6	Clifton Grove (CLI)	0.4	0.4	0.239	0.240	0.013	0.223	0.009
7	Munkerisparken (MUN)	0.46	0.31	0.351	0.362	0.027	0.385	0.018
8	Livry Gargan (LIV)	0.33	0.33	0.174	0.177	0.007	0.178	0.007
9	Luzzi (LUZ)	0.85	0.85	0.58	0.747	0.033	0.589	0.016
10	Vika (VIK)	0.97	0.97	0.652	0.658	0.079	0.682	0.025
11	Miljakovac (MIL)	0.37	0.2	0.2	0.123	0.044	0.120	0.033

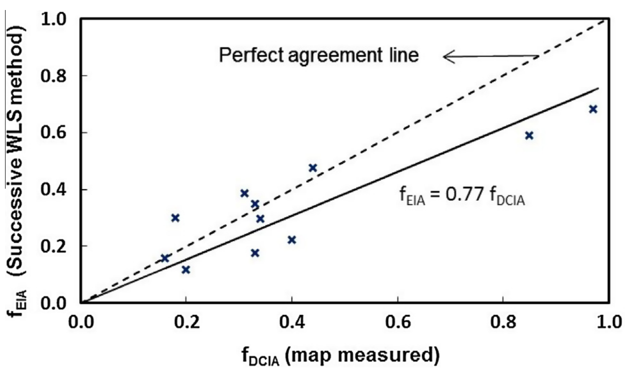

Fig. 3. EIA fraction estimates from the successive WLS method versus map measured DCIA fraction values for the eleven catchments of Boyd et al. (1993).

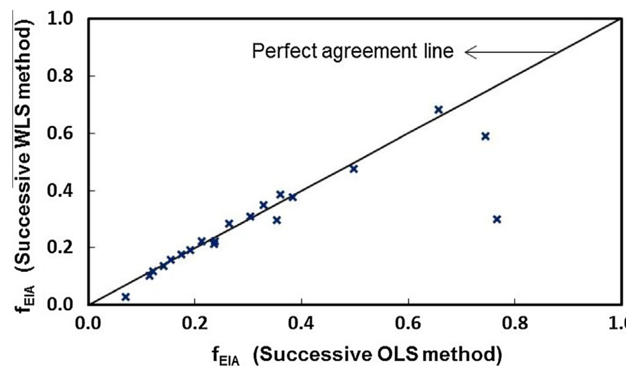

Fig. 4. EIA fraction estimates in the successive WLS method versus EIA fraction estimates in the successive OLS method for the twenty study catchments.

However, the OLS method is less effective in the catchments with the greatest difference between f_{EIA} in OLS and WLS methods. To exemplify, the plots of runoff depth versus rainfall depth for Sarita, Como 3, STR, and LUZ catchments in both the successive OLS and WLS methods are presented in Fig. 6. It is seen that the WLS method has identified combined events in Sarita and LUZ catchments, but the OLS method fails to do so. While the f_{EIA} estimates have decreased from 0.071 and 0.747 in OLS to 0.03 and 0.589 in WLS for Sarita and LUZ, respectively, the decrease in $s(f_{EIA})$ from OLS to WLS is found to be about 89% and 54% in Sarita and LUZ, respectively. Also for STR and Como 3 catchments, Fig. 6 shows a greater number of combined events at larger rainfall depths for the WLS results. The value of f_{EIA} has decreased from 0.768 and 0.116 in OLS to 0.300 and 0.102 in WLS for STR and Como 3, respectively. In addition, 67% and 79% decrease is seen in the $s(f_{EIA})$ values from OLS to WLS for STR and Como 3, respectively. The above results indicate that while the successive OLS method does not

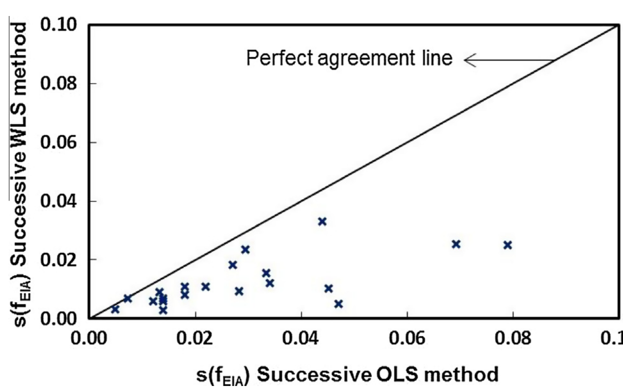

Fig. 5. Standard deviation of the EIA fraction estimates in the successive WLS method versus standard deviation of the EIA fraction estimates in the successive OLS method for the twenty study catchments.

Table 3
Measured TIA fraction, estimated EIA fraction, and standard deviation of the estimated EIA fractions for the nine study catchments in Minnesota, USA in OLS and WLS methods.

Row	Catchment name	f_{TIA}	OLS		WLS	
			f_{EIA}	$s(f_{EIA})$	f_{EIA}	$s(f_{EIA})$
1	Arlington-Hamline Under-Ground Facility (AHUG)	0.507	0.142	0.012	0.137	0.006
2	Golf Course Pond inlet (GCP)	0.438	0.238	0.022	0.213	0.011
3	Como 3	0.405	0.116	0.014	0.102	0.003
4	Sarita wetland inlet (Sarita)	0.367	0.071	0.047	0.030	0.005
5	Trout Brook-East Branch (TBEB)	0.447	0.193	0.014	0.193	0.006
6	East Kittsondale (EK)	0.562	0.385	0.018	0.376	0.011
7	Phalen Creek (PC)	0.587	0.305	0.018	0.310	0.008
8	Saint Anthony Park (SAP)	0.613	0.214	0.014	0.224	0.007
9	Trout Brook Outlet (TBO)	0.473	0.265	0.034	0.284	0.012

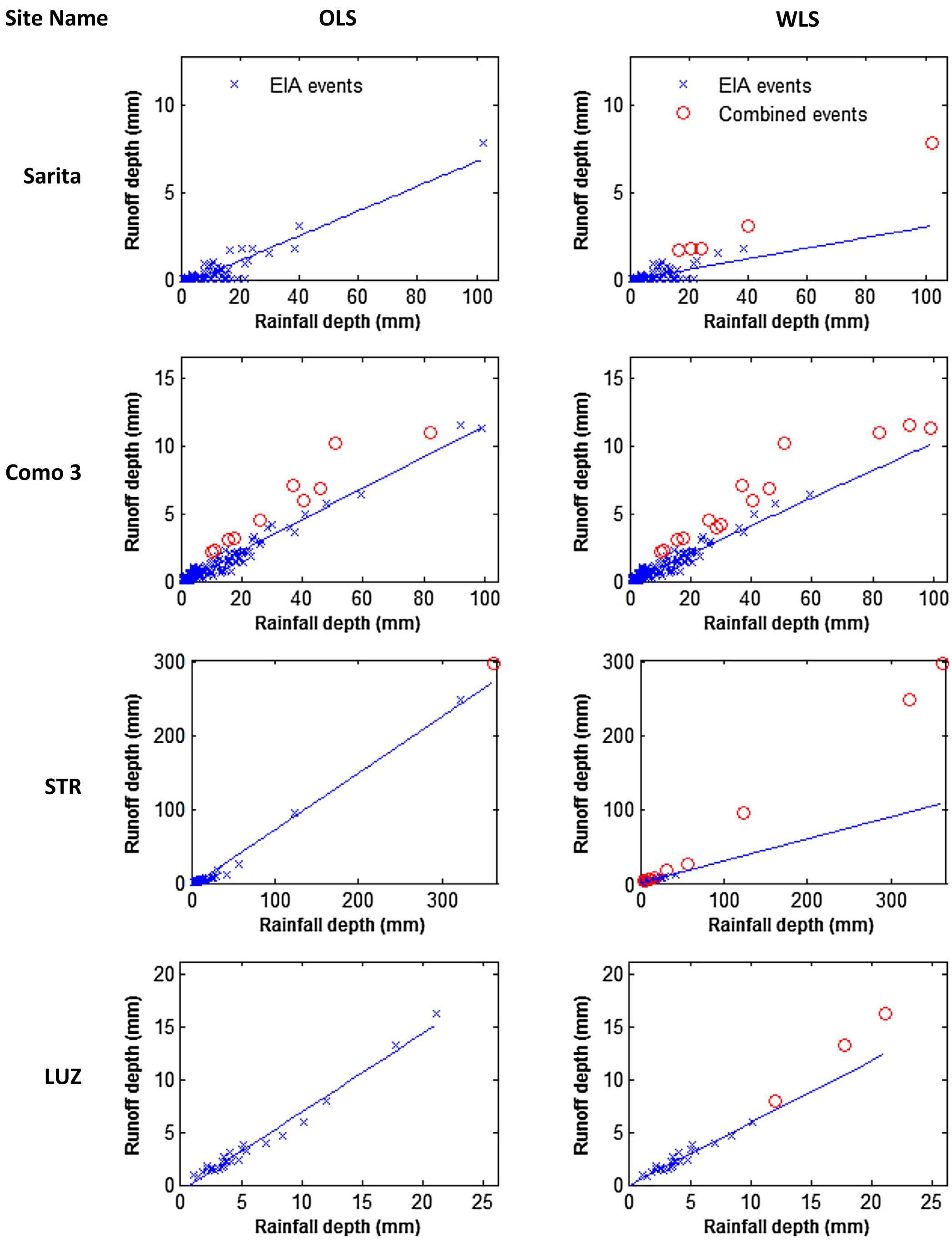

Fig. 6. Runoff depth versus rainfall depth plots in both OLS and WLS methods for Sarita, Como 3, STR, and LUZ catchments.

perform well in some cases, the successive WLS method suitably improves the EIA fraction estimates. Plots of runoff depth against rainfall depth for all the twenty study catchments in the WLS method are presented in Fig. S1 (Appendix A) as supporting information for this paper.

6. Conclusion

The best method to quantify EIA fraction in urban watersheds is the statistical analysis of observed rainfall and runoff data. Improvement in the methods to estimate parameters is important in understanding and predicting runoff in urban catchments. The theoretical framework has been developed using the general linear least square model with a new criterion for categorizing runoff events. Different issues about Boyd's method that reduce the precision of the EIA estimates were then identified, discussed and addressed as:

1. Runoff measurement error is an inevitable issue in the flow monitoring process, which originates from various natural, human and instrument errors. This issue was addressed by proposing a new EIA criterion equal to the maximum of 2 times the standard error of runoff depth and 1 mm for separating EIA events from combined events in the rainfall-runoff data of a catchment.
2. Boyd's method has a subjective component where it investigates the data points corresponding to small rainfall depths separately in order to find f_{EIA} in a catchment. To address this

issue, a method based on successive least square regressions for determining EIA fraction in urban catchments based on rainfall-runoff data and using a general form of EIA criterion was proposed. Two specific cases of the proposed method, ordinary least squares (OLS) and weighted least squares (WLS) methods, were then introduced. Both OLS and WLS methods eliminate the subjective part of Boyd's method and automate the estimation of EIA fraction from rainfall-runoff data.
3. Heteroscedasticity has a negative impact on the precision of the regression parameters. To counteract heteroscedasticity in measured data and improve the precision of EIA fraction estimates, WLS instead of OLS in the successive regression process (i.e., successive WLS method) was proposed. The successive WLS method produced results that were reasonable in comparison to the measured DCIA.
4. The proposed WLS method with the improved EIA criterion is recommended for EIA analysis of all rainfall and runoff records. OLS method with the improved EIA criterion should only be used for homoscedastic conditions where the variance of residuals is not dependent upon the characteristics of the observations.

The improved methods in this study were applied to twenty urban catchments. In contrast to TIA and DCIA, EIA does not require analysis of maps or determination from field investigations. Rainfall and runoff data analysis for catchments with heteroscedastic residuals using the successive WLS method resulted in different f_{EIA} values, lower variance of f_{EIA} estimates, and changes in the categorization of the runoff events (i.e. EIA and combined events). The results revealed that while both of the OLS and WLS methods automate the estimation of EIA fraction from rainfall-runoff data, the WLS method is more robust than the OLS method and generates results that sometimes have substantial differences and are always more precise than the OLS method.

An assessment of the quality of the rainfall-runoff data is recommended prior to the application of the successive OLS and WLS methods. More details on the selection of rainfall events based on uniformity of spatial pattern and removing outliers are presented in Ebrahimian et al. (2016). Additional research is needed to develop criteria for the minimum number of rainfall events or the duration of monitoring records. However, the precision of the regression slope coefficient, defined by its standard deviation, provides insight into the relevant factors. This standard deviation varies among watersheds. It is dependent on the mean square error of the regression, the number of events, and squared deviations between rainfall depths and mean of the events. In the absence of established criteria, and as a general rule based on the authors' experience, at least one year of monitoring data (or ten storm events) is needed to quantify f_{EIA} using the successive OLS and WLS methods.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2016.02.023.

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