Advanced sensitivity analysis of the impact of the temporal distribution and intensity in a rainfall event on hydrograph parameters in urban catchments: a case study

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Abstract. Knowledge of the variability of the hydrograph of outflow from urban catchments is highly important for
15 measurements and evaluation of the operation of sewer networks. Currently, hydrodynamic models are most frequently used for hydrograph modeling. Since a large number of their parameters have to be identified, there may be problems at the calibration stage. Hence, the sensitivity analysis is used to limit the number of parameters. However, the current sensitivity analysis methods ignore the effect of the temporal distribution and intensity of precipitation in a rainfall event on the catchment outflow hydrograph. The article presents the methodology of construction of a simulator of catchment outflow hydrograph
20 parameters (volume, maximum flow). For this purpose, uncertainty analysis results obtained with the use of the GLUE (Generalized Likelihood Uncertainty Estimation) method were used. An innovative sensitivity coefficient has been proposed to study the impact of the variability of hydrodynamic model parameters depending on rainfall distribution, rainfall genesis (in the Chomicz scale), and uncertainty of estimated simulator coefficients on the parameters of the outflow hydrograph. The results indicated a considerable influence of rainfall distribution and intensity on the sensitivity factors. The greater the
25 intensity and temporal distribution of rainfall, the lower the impact of the identified hydrodynamic model parameters on the hydrograph parameters. Additionally, the calculations confirmed the significant impact of the uncertainty of the estimated coefficient in the simulator on the sensitivity coefficients, which has a significant effect on the interpretation of the relationships obtained. The approach presented in the study can be widely applied at the model calibration stage and for appropriate selection of hydrographs for identification and validation of model parameters.

1 Introduction

Climate change and progressive urbanization result in an increase in the volume of stormwater outflow from catchments, which leads to flooding, and deterioration of water quality in receivers (Crocetti et al., 2020; Fletcher et al., 2013). To reduce the incidence of these phenomena, there is a need to runoff model. This can be achieved using hydrodynamic models based on physical equations representing stormwater outflows. One of the common tools is the SWMM (Stormwater Management

35 Model) program (Buahin and Horsburgh, 2015; Crocetti et al., 2020; Gironás et al., 2010). Due to the interactions between parameters identified in the models, they may be difficult to calibrate and the results may be biased. Therefore, statistical models are used for simulation of runoffs, which has been shown in a number of studies (Gernaey et al., 2011; Yang and Chui, 2020). A serious drawback of many models (the so-called black box techniques) is their inability to interpret structural parameters (Zoppou, 2001).

40 The hydrodynamic model must be calibrated to reflect the conditions prevailing in the real system. Calibration of the catchment model is a complex task aimed at determination of the optimal values of parameters with a satisfactory goodness-of-fit of calculation outcomes and measurement results (Bárdossy, 2007; Dotto et al., 2012; Guan et al., 2015). Parameter values are determined for an appropriate form of the objective function in which one or more criteria (maximum instantaneous flow, hydrograph volume, mean relative or absolute error of flow prediction) can be included. Since the description of the stormwater

45 outflow from the catchment is complicated, modeling the phenomenon requires knowledge of many parameters (physical and geographical characteristics of the catchment and the sewer network). A number of these parameters can be determined using detailed spatial data (GIS), as indicated in numerous studies (Fraga et al., 2016; Leandro and Martins, 2016). This helps to reduce the number of variables included in the calibration. However, since a large number of parameters must be included in the models, there may be problems with identification of their values. Therefore, the aim is usually to simplify the calibration

50 process by elimination of factors that have a negligible impact on simulation results. Hence, model sensitivity analysis is employed.

As shown by literature review (Chisari et al., 2018; Tolley et al., 2019; Xu et al., 2019), the analysis is often applied at the stage of calibration of mathematical models. In practice, local and global sensitivity analysis methods, which can be implemented for statistical and physical relationships, are used (Link et al., 2018; Morio, 2011; Cristiano, et al. 2019). In the

55 case of the local sensitivity analysis, the calculations consist in determination of the derivative value at a given point, which is the basis for assessment of the effect of the variance of the variables on the modeled value (Razavi and Gupta, 2015). One of the drawbacks of the local sensitivity analysis is the fact that the variability of the analyzed phenomenon and the effect of variables are considered in the narrow domain of the modeled variable (Pianosi et al., 2016). This approach ignores the fact that the sensitivity of the model in the domain of the output values may change, which may be important for calibration of the

60 model at the validation stage and its course. In the case of non-linear models, the local sensitivity analysis does not take into account the character of the relationships between the explanatory variables and the dependent variable. Then, the sensitivity coefficient is calculated only for the mean level of the explanatory variable. Nevertheless, this method is widely used in the

analysis of the sensitivity of models describing runoff in urban catchments, which has been confirmed by numerous studies (Ballinas-González et al., 2020; Liu et al., 2020; Yang et al., 2019). Another shortcoming of sensitivity analysis based on

65 partial derivatives is the fact that the effects of individual variables on the output variable are estimated with the other variables kept constant. This is rarely observed in the case of complex relationships, as the explanatory variables are then correlated to some extent. The *Cateris Paribus* analysis does not take this fact into account. Consequently, the effects of individual variables may be overestimated.

The global sensitivity analysis does not have many of the aforementioned disadvantages. One of the simplest methods used in

70 many cases is based on multiple linear regression (Ashley and Parmeter, 2020; Touil et al., 2016). However, the results of the sensitivity analysis can be considered reliable when the coefficient of determination reflecting the relationship between the dependent variable and the explanatory variables is not lower than 0.70. When this requirement is not met, other methods for global sensitivity analysis should be applied (Saltelli et al., 2007). Variance methods, which facilitate estimation of the contribution of the individual parameters to the model output variance using the Monte Carlo method, are more precise and

75 more computationally complex. The global sensitivity analysis (GSA) method is one of the commonly used approaches. It has been subjected to modifications, as described in Iooss and Lemaître (2015). Variance methods are currently gaining increasing interest, which is confirmed by the number of publications in this field. However, since implementation thereof is complicated, simplified methods are used in many cases despite the major advantage of variance approaches over the local analysis methods. The implementation of the global sensitivity analysis methods is not a simple task, as it requires complex mathematical tools,

80 which limits their application.

Given the information specified above, the paper presents an original application of the logistic regression method for sensitivity analysis. The advantage of the model is the fact that it has the form of a statistical relationship; hence, without the need for complex analyses, it can be used to determine the effect of parameters included in the calibration of the catchment model, precipitation characteristics, and absolute values of the modeled dependent variables on the parameters of outflow

85 hydrographs (maximum instantaneous flow, hydrograph volume). The approach proposed in the present study also facilitates analysis of the sensitivity of selected explanatory variables, depending on the numerical values of the modeled hydrograph parameters of catchment runoff. At the stage of sensitivity analysis, the effect of the uncertainty of coefficients estimated in the statistical model (logistic regression) on the calculation results is included, which is reflected in the determined sensitivity coefficients. Since the model is constructed based on simulation results provided by the Monte Carlo method, which is typical

90 for global sensitivity analysis methods, this approach can complement and extend the results of GSA calculations. Summing up, the sensitivity analysis used in the present study represents a fusion of local and global sensitivity analysis through combination of logistic regression in phenomenon modeling with partial derivatives. Since logistic regression is not an example of a black-box method, as it has an explicit form of dependence between the modeled probability of success and explanatory variables, the use of partial derivatives for assessment of the sensitivity of the model to individual parameters seems reasonable.

95 Especially in the case of an implicit, complex, and non-linear dependence, it is recommended that variance-based techniques such as the Sobol method should be employed. Partial derivatives used in the logistic regression model increase the flexibility

of this method, as it is possible to assess the model sensitivity to individual parameters at any point in the domain. An additional modification can be the use of a standardized local sensitivity analysis method based on logarithms of dependent and explanatory variables. This facilitates assessment of the effect of the percentage increase in the explanatory variable on the 100 percentage increase in the dependent variable.

2 Study object

The analysis in this study was carried out in a catchment with a total area of 62 ha, located in the south-eastern part of the city of Kielce, central Poland (Fig. 1). Six types of impervious surfaces were distinguished in the catchment: sidewalks, roads, parking lots, greenery, school playgrounds, and roofs (with 72.5% of their area directly connected to the stormwater sewer 105 system). The main canal is 1.6 km long with a diameter in the range of Ø 0.60–1.25 m. Detailed information about the analyzed catchment was provided by Kiczko et al. (2018). The analysis of measurement data (2010–2016) from the catchment distinguished a dry period of 0.16-60 days. The annual precipitation depth was 537–757 mm and the number of days with precipitation was in the range of 155–266. The number of storms per year in the analyzed period ranged from 27 to 47. The area was characterized by an average annual temperature of 8.1–9.6º C and 36–84 snowfall days. The analysis of flow 110 measurement data recorded with the MES1 flow meter revealed that the instantaneous stormwater stream in the dry periods was in the range of 0.001–0.009 m³/s, which indicates an infiltration effect in the sewer network.

Figure 1. Scheme of the hydrodynamic model of the catchment generated in the SWMM program.

The analyzed sewer system consists of 200 manholes and 100 conduit sections with Ø 0.20–1.25 m diameters and longitudinal slopes of 0.1–2.7 %, which gives a retention capacity of 2032 m³. Maning's roughness coefficient for the conduit is in the range of 0.010÷0.018 $m^{-1/3} \cdot s$. The average retention depth is 2.5 mm in the impervious areas and 6.0 mm in the pervious surfaces, which gives a weighted mean of 3.81 mm for the entire catchment. Stormwater is discharged from the catchment through the S1 channel to the diversion chamber (DC), and some part is discharged directly to the stormwater treatment plant (STP) to the filling level $h_m=0.42$ m. After exceeding the h_m value, the stormwater is discharged via the stormwater overflow (OV) into channel S2, which discharges the stormwater into the Silnica River.

As part of the continuous monitoring carried out in 2009–2011, the volume of stormwater outflow from the catchment was measured using a flow meter installed in the S1 channel at a distance of 3.0 m from the inlet to the DW chamber. In turn, in 2015, parallel MES1 and MES2 flow meters were installed in the inlet (S1) and discharge (S2) channels to measure the flow and stormwater level. A detailed description of the stormwater catchment and installed measuring equipment is provided in Szeląg (2016).

The catchment (Fig.1) had previously been analyzed to determine the variability of the quantity and quality of stormwater and the operation of the sewer system based on the catchment hydrodynamic model generated in the SWMM program. The model used in the study was subjected to deterministic (Szelag et al., 2016) and probabilistic (Kiczko et al., 2018) calibration and was used as the basis for the sensitivity analysis. It was also subjected to probabilistic calibration with the GLUE+GSA method (Szelag et al., 2016). The deterministic calibration is perceived in the present study as a computational case where the uncertainty and interaction of calibrated parameters in the SWMM model is omitted. The parameters were determined with the method of successive substitutions to achieve a sufficiently high degree of agreement between the modeled and measured hydrographs.

4 Methodology

4.1 Rainfall and separation of independent rainfall events

The methodology described in the DWA-A 118E (2006) guidelines was adopted in the study to separate independent rainfall events. The interval between successive independent rainfall events was 4 hours. The minimum rainfall depth (3.0 mm) constituting a rainfall event was adopted as in the studies conducted by Fu et al. (2011) and Fu and Butler (2014). Independent rainfall events were distinguished based on series of rainfall (2010–2016) measured at the rainfall station located at a distance of 2 km from the Si9 collector catchment and the definition of a rainfall event specified above. The number of events in the individual study years was estimated at 36 – 58. The rainfall duration (t_r) in the events was 20 – 2366 min, and the length of the dry period was 0.16 ÷ 60 days. The rainfall depth (P_{tot}) in the rainfall events was in the range of 3.0 – 45.2 mm.

4.2 Scheme of model analysis

In the present study, a method of model sensitivity analysis was proposed to predict the stormwater volume (maximum
145   instantaneous flow, hydrograph volume) with the use of logistic regression (Fig. 2). The method presented here represents a
group of sensitivity analysis methods based on empirical models. It was assumed that the variable rainfall distribution may
exert different effects on the sensitivity of the model and induce changes in the calibrated parameters. It was also assumed that
the sensitivity of the model may change as a result of an increase in the maximum instantaneous stormwater flow and the
volume of the outflow hydrograph. Due to the non-linearity between the modeled hydrograph parameters and the calibrated
150   model coefficients, the use of the linear approach is limited (Chan et al., 2018); therefore, the classification model (logit) was
used in the study. Appropriate threshold values of hydrograph parameters constituting the basis for substitution of continuous
values with classes were selected in the model.

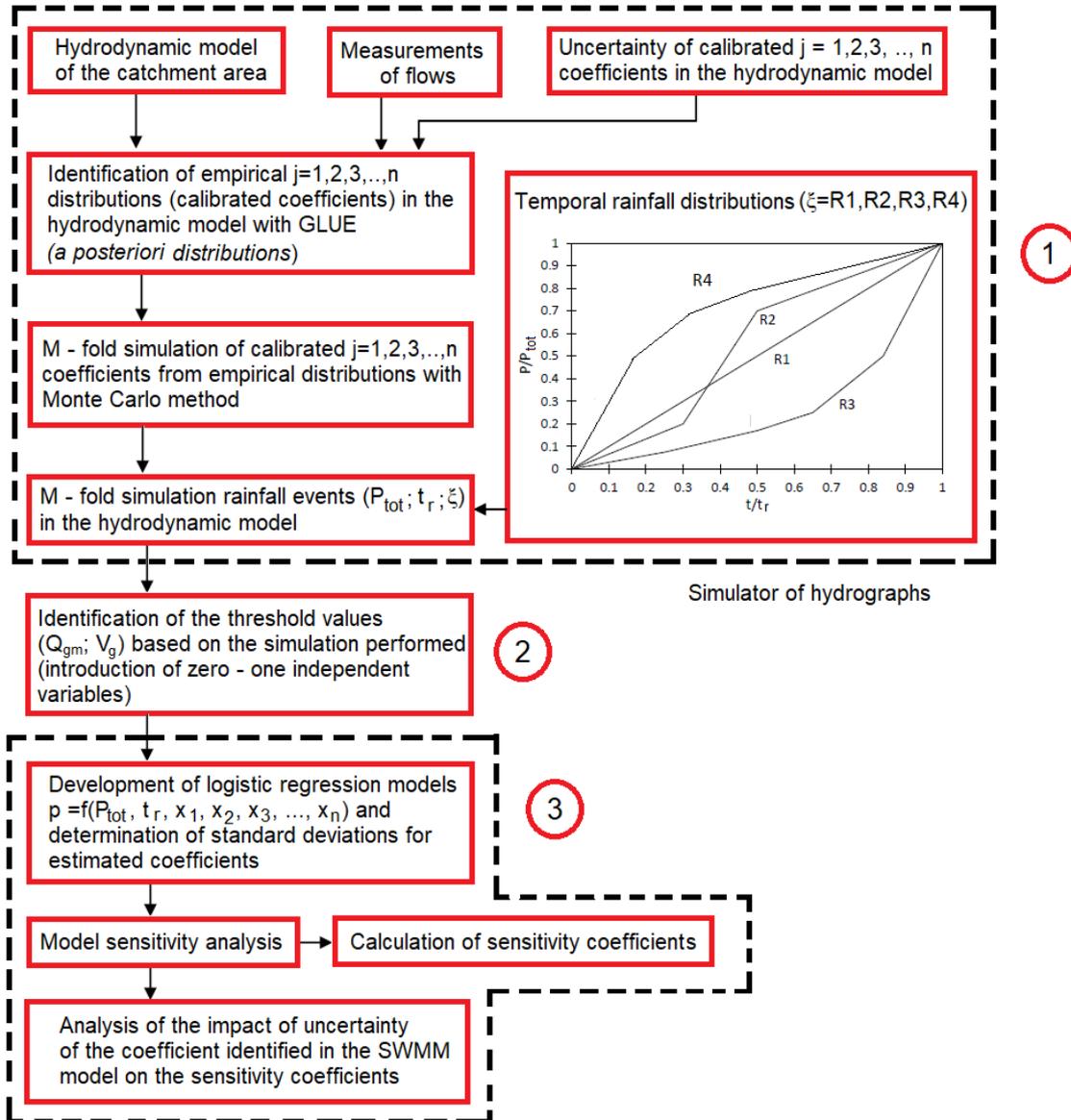
On the one hand, this approach is based on the precipitation dynamics during rainfall events specified in the DWA-A 118E
(2006) guidelines (distribution R1 - constant rainfall intensity during a rainfall event, distribution R2 - maximum rainfall
155   intensity in the middle of the rainfall event, i.e. $t/t_r=0.50$, distribution R3 - maximum rainfall intensity for dla $t/t_r=0.85–1.00$,
and distribution R4 - maximum rainfall intensity the initial phase of rainfall). On the other hand, the modeled hydrograph
parameter values were combined with the rainfall classification, which facilitated generalization of the analysis results.
Compared to the local and global analysis methods, detailed analysis of changes in the sensitivity to the effect of calibrated
coefficients is possible the proposed approach, taking into account values of the modeled parameters of the catchment outflow
160   hydrograph. This has been scarcely considered in this approach so far. The calculation algorithm presented in this study
consists of three elements (Fig. 2). The first one comprises a simulator of parameters of the catchment outflow hydrograph
(statistical model generated with the logistic regression method), which includes rainfall characteristics and coefficients
calibrated in the hydrodynamic catchment model (here: SWMM - Storm Water Management Model).

165   where: calibrated coefficients its mean the same

Figure 2: Calculation algorithm scheme in a logit model.

The simulator was constructed based on simulations performed with the use of calculations in the catchment model, which included the uncertainty of the identified coefficients subjected to calibration. The approach proposed here is applied in

170   computational experiments at the stage of generation of mathematical models for urban catchments, as described by Thorndahl et al. (2009). It is important that the distribution of coefficients (tab. 1) used for GLM identification should result from their

actual variability. The distribution can be determined by probabilistic identification of calibrated coefficients. The GLUE methodology, in which the variability of calibrated coefficients is determined by selecting the so-called behavioral simulations, was employed in this study. Based on *a posteriori* distributions of calibrated coefficients in the catchment model determined

175   by observation data, simulations of catchment outflow hydrographs were performed based on the separated rainfall events in continuous rainfall time series (2010–2016), for which typical rainfall distribution was assumed independently (R1, R2, R3, R4). This was the basis for determination of the outflow hydrograph parameters - maximum instantaneous flow (Q_m) and hydrograph volume (V).

The second stage consisted in establishment of the so-called threshold values of maximum flow ($Q_{m,g}$) and hydrograph volume

180   (V_g), which served as the basis for the division into rainfall events with different intensity and their distribution in the time series (ξ=R1, R2, R3, R4). Establishment of general rules for selection of threshold values may be very difficult, as they are the result of the response of the catchment to the rainfall, which is catchment-specific. These may be characteristic values of flows influenced by the presence of objects in the sewer network (stormwater overflows, etc.) at which they begin to operate. An alternative approach is to apply rainfall classification measures (proposed by Chomicz (1951), Sumner (1988), etc.), which

185   allow determination of the characteristic parameters of hydrographs. The rainfall classes in the Sumner scale determine the extremely different hydraulic conditions prevailing in the sewer network, which may not always be used in practice for measurements and calibration. In the present study, the reference rainfall values determined in the regional classification scale proposed by Chomicz (1951) were the basis for the selection of threshold values (maximum instantaneous flow, hydrograph volume) in accordance with the following equation:

190   $$P_{tot} = U = \alpha_0 \cdot \sqrt{t_r} \qquad\qquad (1)$$

where: t_r – rainfall duration, P_{tot} – rainfall depth equal to its efficiency, α_0 – rainfall efficiency coefficients taking into account the normal, heavy, and torrential rain types.

Based on the Chomicz (1951) classification of rainfall, outflow hydrographs were calculated, their parameters (Q_m, V) were determined, and classification variables were defined. When the calculated values $Q(P_{tot}, t_r, \zeta, \theta)$ and $V(P_{tot}, t_r, \zeta, \theta)$ (where: ζ

195   is a function describing the temporal intensity distribution; θ is a function taking into account the uncertainty of the calibrated parameters in the catchment model) are smaller than the threshold values, they have the value of 0; otherwise, they are equal to 1.

In the third stage, logistic regression models were developed for the values of the explanatory variables (P_{tot}, t_r, ζ, and x_j - values of calibrated coefficients in the catchment model; rainfall characteristics) and for the established dependent (zero-one)

200   variables for the adopted threshold values ($Q_{g,m}$ and V_g) and temporal rainfall distribution (ζ). The subsequent stage of the analyses consisted in determination of the values of the sensitivity coefficients (S_{xj}) in accordance with the methodology described later in this study.

Based on the calculation scheme described above, the paper presents the next stages of construction of a logit model. A catchment model generated in the SWMM program was used for this purpose. The threshold values were determined in

205   accordance with the Chomicz (1951) classification, in which the following categories of rainfall were defined: normal rain

(α₀=1.00), heavy rain (α₀=1.40), and torrential rain (α₀=5.66), assuming a constant temporal rainfall distribution and rainfall duration t_r=15 min. For these assumptions, the depth of rainfall was determined from Eq. (1), and catchment outflow hydrographs were simulated using the calibrated catchment model.

4.3 Logistic regression

210 The logistic regression model, also known as the binomial logit model, is usually employed for analysis of binary data and can be used to determine the probability and identify the occurrence of events (Jato-Espino et al., 2018; Li and Willems, 2019; Szeląg et al., 2020). The maximum amount of stormwater outflow from the catchment and the hydrograph parameters of any rainfall event can be calculated using hydrodynamic models, e.g. SWMM. An alternative solution are statistical models (hydrograph simulators are considerably easier to implement than physical models), for instance the generalized linear model

215 (GLM), which comprises the variability of rainfall characteristics and the uncertainty of calibrated coefficients, shown in the following equation:

$$Q(\mu)_m = \alpha_0 + \alpha_1 \cdot P_c + \alpha_2 \cdot t_d + \alpha_3 \cdot x_1 + \alpha_4 \cdot x_2 + \cdots + \alpha_{j+2} \cdot x_j \qquad (2)$$

where: α_0 – intercept, α_1, α_2, …, α_{j+2} – empirical coefficients determined with the maximum likelihood method, P_{tot} – rainfall depth, t_r – rainfall duration, $x_{1, 2, j=n}$ – calibrated coefficients in the SWMM model, Q_m – link function determining the

220 relationship of the mean value of the dependent variable μ with the linear combination of predictors.

Assuming that μ=p and introducing the link function referred to as logit, it is possible to transform the modeled values of dependent variables included in Eq. (2) into a new (zero-one) system describing the probability values:

$$Q(p) = Q(\mu)_m = logit(p) = \ln\left(\frac{p}{1-p}\right) = exp(\alpha_0 + \alpha_1 \cdot P_{tot} + \alpha_2 \cdot t_r + \alpha_3 \cdot x_1 + \alpha_4 \cdot x_2 + \cdots + \alpha_{j+2} \cdot x_j) \qquad (3)$$

This approach may prove especially useful when the results of calculations in the multiple linear regression model exhibit

225 unsatisfactory convergence ($R^2<0.70$) and it is therefore advisable to introduce classification variables, which is a simplifying solution. Moreover, this approach makes it possible to emphasize and include relationships that might be omitted in the calculations of multiple linear regression, as demonstrated in many reports (Hosmer and Lemeshow, 2000; Kleinbaum and Klein, 2010; Myers et al., 2010). Since the continuous values $Q(P_{tot}, t_r, x_j)_m$ are transformed into the probability space p by the logit function in this case, it is reasonable to equate them with the determined $p(P_{tot}, t_r, x_j)$ values for a given threshold $Q_{g,m}$

230 (Fig. 2). In the transformed data system (expressing probability) varying in the range of 0–1, it was shown that the effect of the change in individual variables (x_j) by Δx_j on the p value is described by the following equation:

$$S_{x_j} = \frac{\partial p}{\partial x_j} \cdot \frac{x_j}{p} = \frac{p(x_{j,g}+\Delta x_j)-p(x_{j,g}; Q_{g,m})}{(x_{j,g}+\Delta x_j)-x_{g,j}} \cdot \frac{x_j}{p(x_{j,g}; Q_{g,m})} = \alpha_{j+2} \cdot x_j \cdot \left(1 - p(x_{j,g}; Q_{g,m})\right) \qquad (4)$$

where: Q, $p(x_{j,g} + \Delta x_j)$ – maximum flow value (Fig. 2a) and the probability of exceeding thereof for value ($x_{j,g} + \Delta x_j$) (Fig. 2b); $Q(x_{j,g})_{m,g}$ – maximum instantaneous outflow from the catchment; $p(x_{j,g}; Q_{m,g})$ – probability of exceeding the threshold value

235     $Q_{g,m}$ for the given explanatory variables (P_{tot}, t_r, x_1, x_2, x_3, …,x_n) equal to p=0.50 (most of the considerations in the present analyses related to the value p=0.50, as this value corresponds to that of $Q_{g,m}$ in the probability scale *p*).

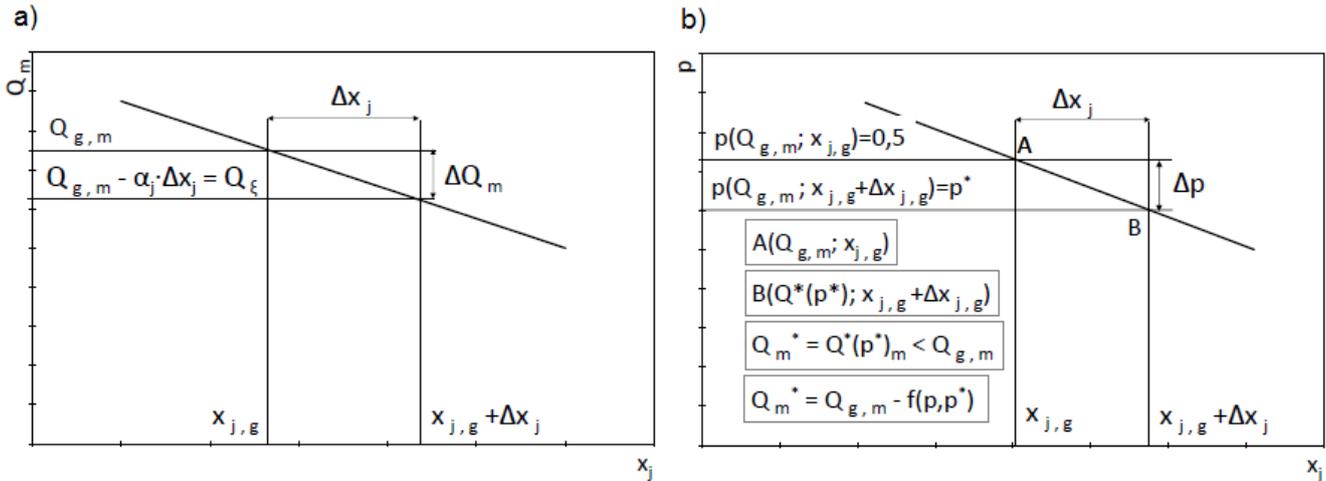



Figure 3: Calculation diagram showing the effect of changes in the $x_{j,g}$ value by Δx_j on (a) the flow volume Q_m; (b) probability of exceeding p($Q_{g,m}$; $x_{j,g}$)=0.50.

240   As indicated in Fig. 3, an increase in $x_{j,g}$ by Δx_j results in a decrease in the $Q_{g,m}$ value by ΔQ_m and yields a flow value of Q_ξ, which facilitates determination of the numerical value of the sensitivity coefficient described by Eq. (4). In the transformed space (see Fig. 2b), the increase in the $x_{j,g}$ value (corresponding to p=0.50 and the threshold value $Q_{g,m}$) to the value of $x_{j,g}$ + Δx_j is accompanied by a decline in the p value by Δp to the value p^*. In these analyses, the determined p^* value corresponds to Q_m^*, which can be defined as $Q_{g,m} - f(p, p^*)$, and the relationship can be expressed as follows:

245
$$S_{x_j} = \frac{Q(x_{j,g}+\varepsilon \cdot \Delta x_j)_m^* - Q(x_{j,g})_{g,m}}{(x_{j,g}+\varepsilon \cdot \Delta x_j)-x_{j,g}} \cdot \frac{x_j}{Q(x_{j,g})_{g,m}} = \frac{f(p,p^*)-Q(x_{j,g})_{g,m}}{(x_{j,g}+\varepsilon \cdot \Delta x_j)-x_{j,g}} \cdot \frac{x_j}{Q(x_{j,g})_{g,m}}$$ (5)

where: ε – empirical coefficient for conversion of the Q_m^* value into p^*. The p^* value can be related to $Q_m^*<Q_{m,g}$; hence, the effect of changes in the x_j value on the calculation results can be inferred and the sensitivity coefficient can be determined from Eq. (5). Assuming a p-value of 0.50 for the analyses was driven by the fact that the logit models determined should be universal, which is important from the point of view of being able to generalise the results obtained and apply them also to

250   other urban catchments (Jato - Espino et al., 2018; Li and Willems 2019; Szeląg et. al., 2020).

The following parameters were included in the assessment of the predictive abilities of logit models: sensitivity– SENS (reflects the correctness of classification of data in a dataset p > p($Q_{g,m}$)), specificity – SPEC (reflects the correctness of classification of data in a dataset p<p($Q_{g,m}$)), and calculation error R_z^2 (reflects the correctness of classification of events at

255   p<p($Q_{g,m}$) and p<p($Q_{g,m}$)), as described in detail by Hosmer and Lemeshow (2000) and Szeląg et al. (2020).

4.4 Analysis of the uncertainty of estimated coefficients in the logit model

The study comprised the analysis of the effect of the parametric uncertainty of the logit models on the results of calculations of probability p as propagation of the uncertainty of the model coefficients. Moreover, the values of the sensitivity coefficients of individual factors S_{xi} were determined. The calculation of uncertainty in the scheme presented in Fig. 1 consisted of the

260 following steps:

- determination of mean coefficient values (α_j) and their standard deviations (σ_j) in logistic regression models used for determination of normal distributions $N(\mu_\alpha, \sigma_\alpha)_i$,
- T-fold sampling of the α_j^* value with the Monte Carlo method based on the developed theoretical distributions N_j,
- determination of probability curves for exceeding the $Q_{g,m}$ value, i.e. $p^*=f(P_{tot}, t_r, \zeta, x_n, N(\mu_\alpha, \sigma_\alpha))$ and sensitivity

265 coefficients $S_{xi}^*=F(P_{tot}, t_r, \zeta, x_n, N(\mu_\alpha, \sigma_\alpha))$ from Eq. (4) as well as the relevant percentiles.

On the basis of the determined logit models for the assumed cut-off thresholds $Q_{g,m}$ depending on the temporal rainfall distribution (ζ), probability curves described by Eq. (3) were plotted and the values of sensitivity coefficients S_{xi} were determined from Eq. (4) for individual explanatory variables.

4.5 GLUE (Generalized Likelihood Uncertainty Estimation)

270 The model uncertainty was estimated using Generalized Likelihood Uncertainty Estimation (Beven and Binley, 1992). It was assumed that model uncertainty can be described by the random variability of its calibrated coefficients. The coefficients variability ranges for the SWMM of the Kielce basin were investigated in previous studies (Kiczko et al., 2018; Szelag et al., 2016). They are shown in Table 1. In the previous studies conducted by Kiczko et al. (2018) and Szeląg et al. (2016), the parameter identification was performed along with the Bayesian approach, using likelihood functions. The parameters were

275 identified on the basis of Bayesian estimation (Beven and Binley, 1992):

$$P(Q/\theta) = \frac{L(Q/\theta)P(\theta)}{\int L(Q/\theta)P(\theta)d\theta} \qquad (6)$$

where $P(\theta)$ stands for a priori (Table 1) calibrated coefficients distribution (uniform distribution was applied in the present study), $L(Q/\theta)$ a likelihood function used to calculate weights for the Monte Carlo sample, depending on the model fit to the observed basin flows Q and $P(Q/\theta)$ resulting in a posteriori distribution of model coefficients θ. The following formula was

280 used as the likelihood function (Romanowicz and Beven 2006):

$$L(Q/\theta) = exp\left(\frac{\sum_{i=1}^{N}(Q_i-\widehat{Q_i})^2}{\kappa \cdot \sigma^2}\right) \qquad (7)$$

where Q_i and $\widehat{Q_i}$ -i-th value from the times series of observed and computed flows; κ is the scaling factor for the variance σ^2 of model residuals, used to adjust the width of the confidence intervals. In the study conducted by Kiczko et al. (2018), the value of κ was determined, ensuring that 95% of observed flow points are enclosed by 95% confidence intervals of the model

285 output.

The coefficients in the ranges given in Table 1 were uniformly sampled 5000 times, and the model was evaluated for each set. The simulation goodness-of-fit was determined as the standard deviation of computed and observed outflow hydrographs. The behavioral simulations were selected using a threshold value of deviation, i.e. simulations with poorer fit were rejected. The threshold value was determined iteratively to ensure that confidence intervals explained the model uncertainty in respect of the observation. The goal was to enclose 95% observation points within 95% confidence intervals. Confidence intervals were calculated on the basis of empirical cumulative distribution functions of an ensemble of modeled hydrographs. The value of the threshold was iteratively increased to reach the above assumption.

Table 1. Ranges of SWMM model coefficients (Kiczko et al., 2018)

Parameters	Unit	Range
Coefficient for flow path width (α)	–	2.7−4.7
Retention depth of impervious areas (d_{imp})	mm	0.8−4.8
Manning roughness coefficient for impervious areas (n_{imp})	$m^{-1/3}{\cdot}s$	0.010−0.022
Manning roughness coefficient for sewer channels (n_{sew})	$m^{-1/3}{\cdot}s$	0.010−0.048

Coefficients were identified and the threshold was adjusted for two rainfall events of 24 July 2011 and 15 September 2010. The size of the behavioral set was as 5000. It should be noted that it is assumed in the above approach that the simulations from the behavioral set are equally probable. In this study, analyses were limited to four parameters in the SWMM model. This is because the calculations performed by Szeląg et al. (2016) for the study catchment showed that the coefficients in the Horton's model as well as the Manning's roughness coefficient and the retention depth of pervious area have an insignificant influence on the results of the catchment outflow hydrograph calculations. With precise spatial data about the catchment, it was shown that the uncertainty in the identification of impervious areas also has a insignificant influence on the modeled outflow hydrogram (Szeląg 2013, 2016). Based on the continuous rainfall series from the period of 2010–2016 and the determined *a posteriori* distributions of calibrated coefficients in the SWMM model, simulations of the combinations of numerical values [α, n_{imp}, d_{imp}, n_{sew}] (5000 samples) were carried out, which facilitated determination of catchment outflow hydrographs (Fig. 3B, Appendix). On this basis, parameters, i.e. maximum instantaneous outflow (Q_m) and volume (V), were determined for each calculated hydrograph. The results of these analyses were used for development of logit models for the established threshold values ($Q_{g,m}$, V_g) and the assumed temporal rainfall distributions (R1, R2, R3, R4). In the knowledge that the number of rainfall events in the period (2010 - 2016) is 321 rainfall events, 1605000 rainfall event simulations were performed (considering the uncertainty of the SWMM model) of which 120000 episodes were separated for logit model validation.

4.6 Hydrodynamic model

The SWMM 5.1 model was used to simulate the outflow from the catchment. The hydrodynamic model considered in this study consists of 92 partial catchments, 200 manholes, and 72 conduit sections. The proportion of impervious areas in the

315 individual sub-catchments ranges from 5% to 90%, and the average slope of the area is 0.5−6%. The surface area of the partial catchments varies from 0.12 ha to 2.10 ha. After calibration, the Manning roughness coefficient for the sewer channels had a value n_{sew}=0.018 $m^{-1/3}$·s, the roughness coefficient and retention depth for the impervious areas were n_{imp}=0.020 $m^{-1/3}$·s and d_{imp}=1.65 mm, respectively, and the flow path width expressed as $W=α_S·A^{0.50}$ was $α_S$=2.00 (Kiczko et al., 2018).

The analyzed catchment model was calibrated and used in the analysis of the quantity and quality of stormwater outflow from

320 the catchment, the operation of stormwater treatment plant, and the function of the stormwater system, which was reported in detail by Szeląg et al. (2016) and Kiczko et al. (2018). The sensitivity analysis and calibration of the catchment model were performed with the GLUE+GSA method as well (Szeląg et al., 2016).

4.7 Verification of generated logit models for analysis of hydrograph parameters

The suitability of the generated logit models for simulation tasks in the case of the stormwater catchment analyzed in the study

325 was verified vs. measurement data. Since the temporal rainfall distributions in the rainfall events derived from measurements varied, they were assessed and adjusted to the theoretical distributions presented in this study (see Fig. B1 – Appendix B) based on the value of the correlation coefficient (R) expressing the goodness-of-fit of empirical distributions $\frac{P}{P_t} = f\left(\frac{t}{t_r}\right)$ to the theoretical distributions (R1, R2, R3, R4).

5 Results and discussion

5.1 Establishment of threshold values

330 The values of calibrated parameters shown in Table 1 served for the SWMM model calculations. Assuming rainfall intensity values corresponding to normal ($P_{tot,u}$=3.7 mm), heavy ($P_{tot,m}$=5.8 mm), and torrential ($P_{tot,g}$=21.9 mm) rain, outflow hydrographs were determined for t_r=15 min; the Q(t) values were determined with at 10-s resolution. The simulations revealed the following values of maximum instantaneous flow and hydrograph volumes: $Q(q_u)_m$=0.275 m^3/s and $V(q_u)$=450 m^3,

335 $Q(q_s)_m$=0.735 m^3/s and $V(q_s)$=812 m^3, and $Q(q_g)_m$=2.95 m^3/s and $V(q_g)$=3500 m^3. It is worth noting that the values of the catchment outflow hydrographs were identical with the rainfall intensity distributions R1, R2, R3, and R4, as demonstrated by Szeląg et al. (2016).

5.2 GLUE (Generalized Likelihood Uncertainty Estimation)

Parameters were identified using outflow time series for two rainfall events of 24 July 2011 and 15 September 2010 (Kiczko

340 et al., 2018). The threshold value of the correlation coefficient ensuring that 95% of the observations were enclosed within

95% confidence intervals was 0.920. The size of the behavioral obtained set was 3375. The confidence intervals were verified for two rainfall events of 30 May 2010 and 30 July 2010 (see Fig. B2 – Appendix B). The percentage values of the enclosed observation points were as follows: 30 May 2010: 91% and 30 July 2010: 47% (Kiczko et al., 2018). The poorer performance for 30 July 2010 results from the bias of the model output, whereas the maximum stormwater flows were predicted correctly.

345 ## 5.3 Estimation of coefficients in the logit model and assessment of goodness-of-fit

Based on the determined values of the dependent variables and the corresponding explanatory variables (P_{tot}, t_r, α, d_{imp}, n_{imp}, n_{sew}) for the assumed rainfall distributions (R1, R2, R3, R4), logit models were generated for calculation of the probability of exceeding the threshold values: maximum instantaneous flows ($Q_{g,m}$) and outflow hydrographs (V_g). Table 2 presents the determined values of empirical coefficients (α_j) and assessment of the goodness-of-fit of the calculation vs. measurements

350 results in the logit models used for calculation of $p=F(Q_{m,g})$ and $p=F(V_g)$. The calculations indicated identical coefficient values in the case of temporal rainfall distributions R3 and R4 in the logit model; hence, the tables below show the results for temporal rainfall distribution R3. The analysis of the goodness-of-fit of the calculation results to the measurement results (SPEC, SENS, R_z^2) revealed that the proposed logit models were characterized by satisfactory classification abilities.

355 **Table 2: Calculated coefficients (α_j) and measures of the goodness-of-fit of measurement results to the logit model calculations of the $Q_{g,m}$ and V_g values for rainfall distributions R1, R2, R3 and R4.**

Rainfall distribution R1						
Variable	$Q(q_u)_{g,m}$		$Q(q_s)_{g,m}$		$Q(q_g)_{g,m}$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
α_0	**-0.235**	0.083	**-23.72**	6.749	**5.051**	1.327
α	**2.571**	0.988	**1.901**	0.821	**0.091**	0.028
d_{imp}	**-1.344**	0.413	**-1.13**	0.473	**-0.129**	0.035
n_{imp}	**-234.241**	84.098	**-7.481**	2.593	**-5.449**	2.057
n_{sew}	**-205.159**	141.19	**-377.74**	107.016	**-419.281**	81.495
P_{tot}	**3.821**	0.913	**2.797**	1.157	**0.249**	0.022
t_r	**-0.221**	0.051	**-1.125**	0.139	**-0.1**	0.009
	SPEC=96.51;		SPEC=100;		SPEC=95.74;	
	SENS=99.79;		SENS=99.77;		SENS=97.62;	
	R_z^2=99.51		R_z^2=99.82		R_z^2=96.28	
Rainfall distribution R2						
Variable	$Q(q_u)_{g,m}$		$Q(q_s)_{g,m}$		$Q(q_g)_{g,m}$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)

Variable						
α_0	**-1.307**	0.465	**-3.509**	0.785	**6.582**	1.386
α	**1.503**	0.491	**1.444**	0.567	**0.29**	0.12
d_{imp}	**-2.971**	0.542	**-2.872**	0.905	**-0.029**	0.015
n_{imp}	**-68.921**	29.814	**-56.207**	26.698	**-22.629**	10.949
n_{sew}	**-114.428**	53.26	**-397.451**	132	**-666.661**	88.012
P_{tot}	**2.792**	0.355	**3.867**	0.81	**0.468**	0.044
t_r	**-0.052**	0.007	**-0.207**	0.043	**-0.092**	0.009
	SPEC=97.43;		SPEC=99.28;		SPEC=98.06;	
	SENS=98.97;		SENS=99.57;		SENS=98.13;	
	R_z^2=98.66		R_z^2=99.48		R_z^2=98.10	

Rainfall distribution R3

Variable	$Q(q_u)_{g,m}$		$Q(q_s)_{g,m}$		$Q(q_g)_{g,m}$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
α_0	**-3.842**	0.98	**-2.908**	0.916	**1.726**	0.675
α	**1.285**	0.283	**1.175**	0.259	**0.312**	0.043
d_{imp}	**-1.869**	0.3	**-1.22**	0.25	**-0.152**	0.043
n_{imp}	**-97.252**	20.082	**-70.814**	18.365	**-20.008**	3.15
n_{sew}	**-161.108**	32.34	**-197.528**	36.361	**-264.179**	40.089
P_{tot}	**3.068**	0.261	**1.959**	0.164	**0.267**	0.017
t_r	**-0.022**	0.002	**-0.046**	0.004	**-0.027**	0.002
	SPEC=95.79;		SPEC=95.92;		SPEC=97.60;	
	SENS=97.11;		SENS=96.11;		SENS=96.89;	
	R_z^2=96.93		R_z^2=96.01		R_z^2=97.25	

Rainfall distribution R1, R2, R3, R4

Variable	$V(q_u)_g$		$V(q_s)_g$		$V(q_g)_g$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
α_0	**-27.793**	3.511	**-23.483**	2.997	**-20.903**	4.516
α	**5.427**	1.963	**3.142**	0.917	**2.837**	0.688
d_{imp}	**-3.983**	0.968	**-3.075**	1.381	**-1.978**	0.722
n_{imp}	**-48.794**	21.066	**-40.105**	21.133	**-31.321**	14.474
n_{sew}	**-86.986**	46.889	**-66.569**	32.38	**-42.606**	20.799
P_{tot}	**7.417**	2.824	**6.904**	1.726	**2.473**	0.391
t_r	**-0.001**	0.001	**-0.001**	0.0003	**-0.001**	0.008

SPEC=96.53;	SPEC=98.63;	SPEC=97.63;
SENS=99.17;	SENS=97.77;	SENS=98.77;
R_z^2=98.73	R_z^2=98.13	R_z^2=98.33

As shown in Table 2, not less than 95.79% of the cases were correctly identified at the calculated value of $p<p(Q_{g,m}; V_g)$ and $p \geq p(Q_{g,m}; V_g)$. The model was validated on 40000 independent rainfall events, for R1, R2, R3, R4 rainfall distribution (Table 3).

Table 3. Results of validation of logit models shown in Table 2

Rainfall distribution R1

Data to validation	$Q(q_u)_{g,m}$		$Q(q_s)_{g,m}$		$Q(q_g)_{g,m}$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
40000	SPEC=96.00; SENS=95.60		SPEC=94.11; SENS=96.20		SPEC=96.20; SENS=95.20	

Rainfall distribution R2

Variable	$Q(q_u)_{g,m}$		$Q(q_s)_{g,m}$		$Q(q_g)_{g,m}$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
40000	SPEC=97.30; SENS=96.50		SPEC=96.20; SENS=95.22		SPEC=95.20; SENS=96.50	

Rainfall distribution R3

Variable	$Q(q_u)_{g,m}$		$Q(q_s)_{g,m}$		$Q(q_g)_{g,m}$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
40000	SPEC=95.50; SENS=97.10		SPEC=96.45; SENS=96.56		SPEC=97.12; SENS=96.45	

Rainfall distribution R1, R2, R3, R4

Variable	$V(q_u)_g$		$V(q_s)_g$		$V(q_g)_g$	
	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)	Values (α_j)	SD (σ_j)
120000	SPEC=95.25; SENS=96.15		SPEC=96.03; SENS=93.17		SPEC=95.03; SENS=96.34	

The results of calculations of the goodness-of-fit measures of the logit models for the temporal rainfall distributions R1, R2, R3, R4 associated with the normal, heavy, and torrential rains confirm the high goodness-of-fit of the calculated and measured results. This confirms the suitability of the models for further analyses.

5.4 Verification of the generated logit models vs. measurement data

The analyses showed that, in 237 of the 248 events for which the empirical and theoretical rainfall distribution exhibited high convergence ($R \geq 0.96$), the calculation results from the logit models were consistent with the simulation data provided by the

370 SWMM model in terms of the Q_m classification. In the total number of the 248 rainfall events, the R1 temporal rainfall distribution was identified in 126 events (calculation results consistent with measurements in 122 events), 72 events represented the R2 temporal distribution (calculation results consistent with measurements in 69 events), and 58 events were determined as the R3 and R4 temporal distributions (simulation results consistent with measurements in 56 events). In the other 73 events (with R<0.96), the results of calculations performed in the logit models agreed with measurement results in 43

375 events. In this group of events, 19 rainfall events were classified as the R1 temporal distribution (simulation results consistent with measurement results in 8 events), 23 events represented the R2 temporal distribution (calculation results consistent with measurement results in 17 events), 31 events were identified as the R3 and R4 temporal distributions (simulation results consistent with measurements in 18 events). The V_g value calculated for 321 rainfall events agreed with the measurement results obtained for 281 events. Table 4 shows a comparison of the calculation results provided by the proposed logit models

380 with the measurement results obtained in the consecutive years (2010–2016).

The table shows the agreement of the calculation results for the hydrograph parameters obtained via simulation with the SWMM model and logistic regression with regard to the classification of maximum flows and hydrograph volumes. The data presented in Table 4 indicate agreement of the logit model-based calculation results with the measurement results.

385 **Table 4. Comparison of measurement and calculation results in the analyzed period**

Year	M	$Q_m^{mes}<0.3$	$Q_m^{sim}<0.3$	$Q_m^{mes} > 2.5$	$Q_m^{sim} > 2.5$	$Q_m^{mes}<0.75$	$Q_m^{sim}<0.75$	$Q_m^{mes} > 0.75$	$Q_m^{sim} > 0.75$
		$V(Q=0.3 \text{ m}^3 \cdot \text{s}^{-1})$		$V(Q=2.5 \text{ m}^3 \cdot \text{s}^{-1})$		$V(Q=0.75 \text{ m}^3 \cdot \text{s}^{-1})$			
2010	47	18/15	20/18	3/9	3/6	30/24	22/20	17/23	15/19
2011	51	20/23	15/19	2/7	2/5	29/28	26/23	22/23	18/16
2012	36	15/17	12/14	3/7	2/6	22/20	18/18	14/16	11/18
2013	41	20/18	16/15	4/8	3/9	28/22	24/20	13/19	10/22
2014	44	18/15	14/12	3/8	2/8	29/25	26/22	15/15	12/13
2015	58	23/18	18/22	3/9	3/10	39/32	33/29	19/26	15/23
2016	44	24/17	22/13	4/9	4/7	34/25	30/22	10/19	12/17

where: x1/x2 – number of rainfall events in a year with an exceeded x1=$Q_{g,m}$/x2=V_g threshold value; calibrated values α, n_{inp}, d_{imp}, n_{sew} specified in section "Hydrodynamic model" were used for verification calculations in the logit models shown in Table 4.

390 The calculation results confirm that the proposed logit models include the key determinants of the variability of hydrograph parameters, which has been confirmed in theoretical studies and results of field studies conducted by many authors (Gironás et al., 2010; Guan et al., 2015; Thorndahl, 2009). The maximum difference between the number of rainfall events where the parameters of the catchment outflow hydrograph were identified correctly based on rainfall distribution and rainfall

characteristics by the logit model and the calibrated values of the SWMM model is 6 events, which was noted for 2015. In this
395   case and in the other years, this is associated with problems with agreement between empirical and theoretical distributions
specified in DWA-A 118E (2006). This is confirmed by the local nature of the dynamics of rainfall events in some urban
catchments in Europe, as reported by various authors (De Paola and Ranucci, 2012; Todeschini et al., 2012) investigating the
variability of temporal rainfall distribution in a rainfall event. Hence, there is a need to construct regional rainfall models that
take into account the variability of measured rainfall distribution in an event rather than that assumed for another region
400   (Wartalska et al., 2020). However, this may be the only solution in the absence of measurement data, which has been confirmed
in studies on the use of typical DWA-A 118E (2006) of rainfall distributions to model the sewer network operation (Siekmann
and Pinnekamp, 2011). Analysis of the data compiled in Table 3 demonstrates that, in addition to their theoretical value and
the possibility to determine sensitivity (Q_m, V_g), the proposed models can be used for identification of an event with a
probability of exceeding the $Q_{m,g}$ or V_g values in the analyzed catchment.

405   The analyses performed in the study (Table 2) indicate a strong effect of the flow path width (α), Manning roughness coefficient
of impervious areas (n_{imp}), retention depth of impervious areas (d_{imp}), and Manning roughness coefficient of sewer channel
(n_{sew}) on the hydrograph volume and the maximum instantaneous stormwater stream outflow in the analyzed catchment. This
is confirmed by the values of the α_j coefficients. The other explanatory variables (Table 1) are statistically insignificant at the
assumed confidence level of 0.05. These findings were confirmed by Barco et al. (2008), Kleidorfer et al. (2009), Skotnicki
410   and Sowiński (2015), who calibrated hydrodynamic models of catchments in the USA (Santa Monica; area catchment of 217
km^2), Australia (Melbourne; area catchments of 37.98 ha and 89.10 ha), Poland (Poznań; area catchment of 6.7 km^2). The
present simulation results confirm the findings reported for larger catchments located in China (Li et al., 2014), where
correlation coefficient values and entropy measures were used, the USA (Muleta et al., 2013), where the GLUE method was
applied, and Iran (Rabori and Ghazavi, 2018), where the local sensitivity analysis was carried out. The analysis of the values
415   of coefficients α_j in the logit models indicates that only an increase in the flow path width (α) leads to an increase in the
probability of exceeding $Q_{g,m}$ as well as V_g, which is confirmed by the analyses performed by Barco et al. (2008). An inverse
correlation was found for the other parameters in the SWMM model (n_{imp}, d_{imp}, n_{sew}). The results of the n_{sew} simulations relative
to $Q_{g,m}$ and V_g are confirmed by the calculations reported by Barco et al. (2008) and Li et al. (2014). The catchment analyzed
by Li et al. (2014) was situated in China (Changsha city, area catchment of 11.7 ha). The impervious area accounted for 56%
420   of the catchment. The increase in the n_{sew} value reported by many authors (Barco et al., 2008; Fraga et al., 2016; Li et al., 2014)
indicated an opposite relationship to that observed in this study. This shows that an increase in the n_{sew} value results in a shorter
stormwater flow time and accumulation of flow from channels, which leads to a rise in the stormwater level and reduction of
the instantaneous flow stream in the cross-section closing the catchment (Leandro and Martins, 2016). The calculations
performed by Li et al. (2014) confirmed the $Q_m=f(n_{imp})$ relationship obtained in the study; however, these analyses did not
425   include the rainfall distribution and genesis. The n_{imp} and d_{imp} simulation results obtained in the study are relevant in the
nonlinear reservoir SWMM model for simulation of the catchment outflow (Gironás et al., 2010; Rossman, 2015). An increase

in the catchment retention leads to a reduction in the amount of stormwater flowing into the sewer channels, which has an impact on the simulation results of the outflow in the cross-section closing the catchment.

5.4.1 Sensitivity coefficients (hydrograph volume vs. maximum instantaneous flow)

430 The plotted curves indicated that the smaller the volume of the calibrated catchment outflow hydrograph, the greater the sensitivity of the model to changes in the calibrated coefficients identified in the catchment model (Fig. 5a–d). As part of the present calculations, the effect of the rainfall intensity distribution (ξ) and the threshold value ($Q_{g,m}$ and V_g) on sensitivity coefficients S_{xj} was assessed. The analyses focused on the temporal R2 distribution, i.e. Euler type II, as this distribution is used for assessment of the effectiveness of the operation of sewer networks (Siekmann and Pinnekamp, 2011) and is thus

435 highly important in engineering considerations. The analyses of the subsequent rainfall distributions (R1, R2, R3, R4) were based on the maximum flow caused by normal rainfall ($Q=0.3$ m^3/s), which is determined by the occurrence of stormwater overflow in the case of the above-mentioned value. The results of these analyses are presented in Fig. 4–5.

The analysis of the results of calculations of the probability of exceeding the threshold values V_g revealed that the rainfall intensity distribution did not influence the model sensitivity, which was confirmed by simulation experiments in the analyzed

440 urban catchment (Szelag et al., 2016). The plotted curves (Fig. 5) indicated that the calibrated volume in the domain of the V_g value exhibits the greatest sensitivity (deterministic solution) to changes in d_{imp} and α. This relationship was confirmed by Skotnicki and Sowiński (2015), who simulated outflows from a 6.7 km^2 catchment in Poznań and employed local sensitivity analysis. Similar results were also obtained by Rabori and Ghazavi (2018) in their analyses of a catchment outflow in Iran. These correlations were also confirmed by the calculations reported by Mrowiec (2009), who modeled hydrographs in the

445 urban catchment in Częstochowa (120 ha). The present analysis results were also are confirmed by Ballinas-Gonzáles et al. (2020), who demonstrated a major impact of the characteristics of impervious areas on the variability of the catchment outflow hydrograph. Different sensitivity analysis results were reported by Li et al. (2014), who demonstrated a crucial effect of n_{sew} on the outflow hydrograph volume. Among the explanatory variables considered in this study (for any p in Eq. (4)), n_{imp} was found to exert the lowest effect on the probability of exceeding V_g at any p value. The course of the curves and their variability

450 (Fig. 5) indicate the lowest S_{xi} values of the calibrated coefficients (α, n_{imp}, d_{imp}, n_{sew}) catchment outflow hydrographs in the case of torrential rainfall events, whereas the highest values were noted in the case of normal rainfall events (in the Chomicz scale).

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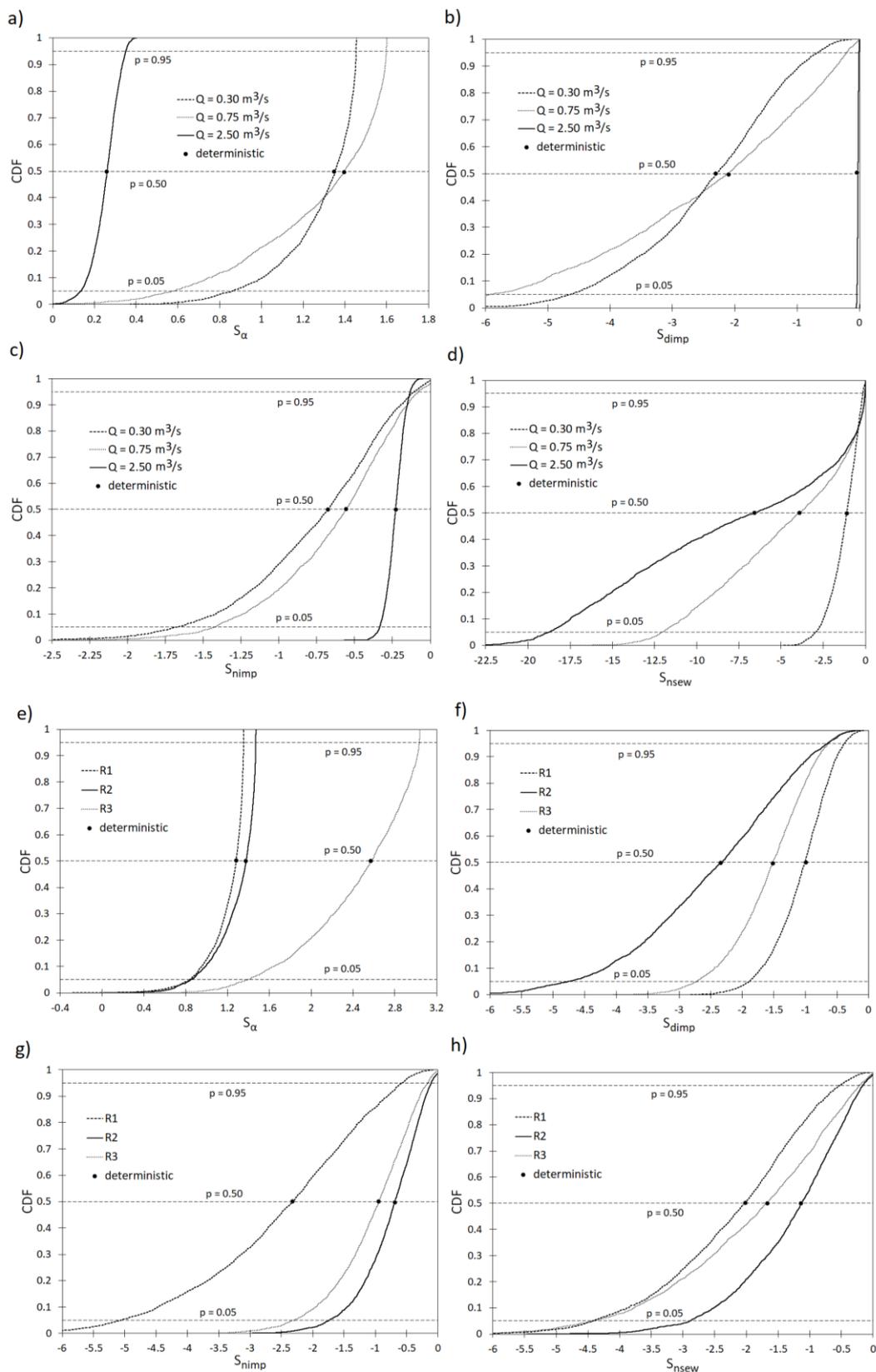


Figure 4. Comparison of calculation results (deterministic and probabilistic solutions) of sensitivity coefficients (S$_\alpha$, S$_{dimp}$, S$_{nimp}$, S$_{nsew}$)
for (a–d) threshold values (Q=Q$_{g,m}$) and temporal rainfall distribution ξ=R2; (e–h) temporal rainfall distributions (ξ=R1, R2, R3)
for Q$_{g,m}$=0.30 m³/s.

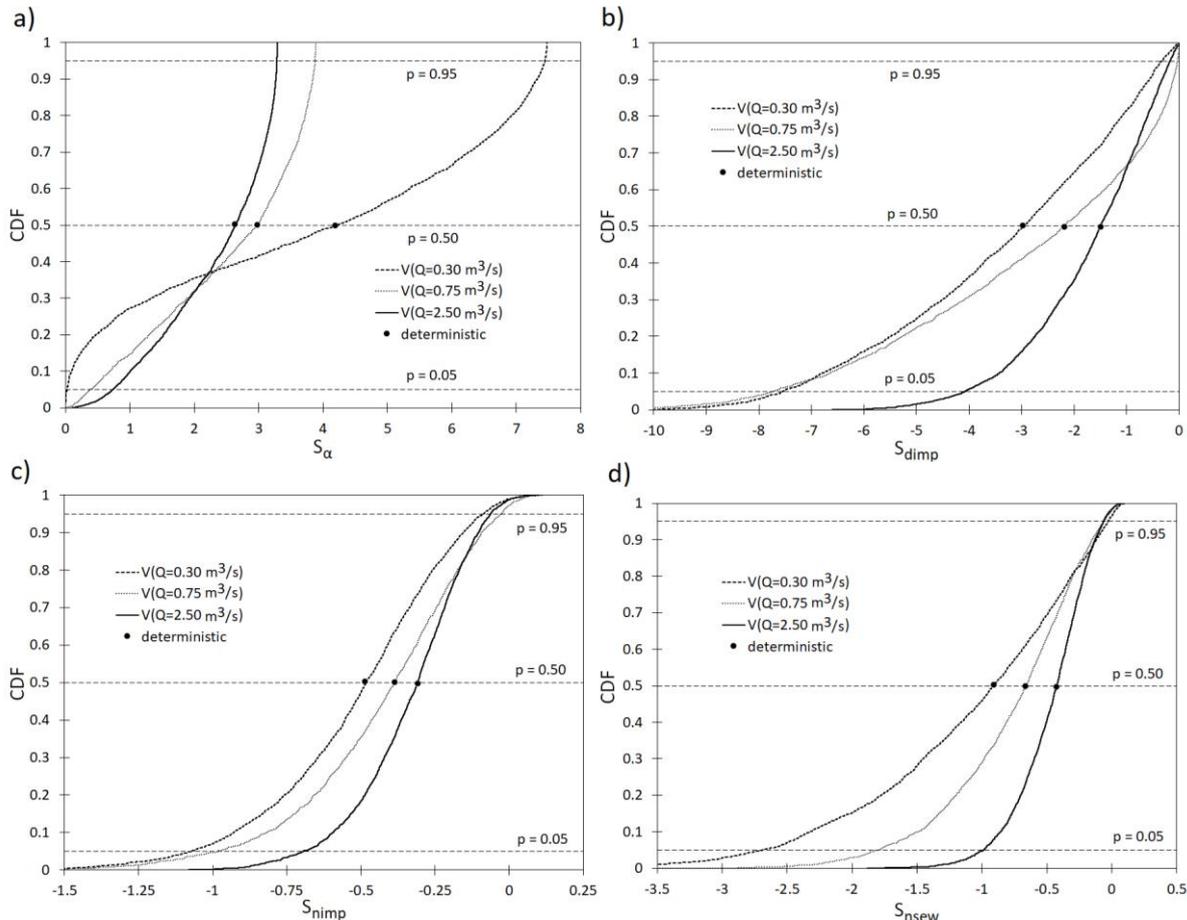



Figure 5: Comparison of calculation results (deterministic and probabilistic solutions) of sensitivity coefficients (S$_\alpha$, S$_{dimp}$, S$_{nimp}$, S$_{nsew}$)
for (a ÷ d) threshold values V(Q)=V$_g$ and temporal rainfall distribution ξ=R1, R2, R3.

In terms of the selection of hydrographs for calibration followed by validation (SWMM model), the present results have an engineering aspect. This is associated with the fact that different relations V(Q)=f(x$_i$) can be obtained by validation of the model coefficients at the calibration stage, which is crucial for minimization of the difference between measurement and simulation values.

5.4.2 Sensitivity coefficient (maximum instantaneous flow vs. rainfall distribution)

Based on the plotted curves (probabilistic solution), it can be concluded that, when the Q$_m$ value is calibrated in the region of Q$_{g,m}$=0.30 m³·s^{-1} (uniform rainfall distribution R1, normal rain), the model shows the greatest sensitivity (percentile 0.50) to changes in n$_{imp}$ (deterministic solution), as confirmed by the value S$_{nimp}$= -2.47 (Fig. 4g). The Manning roughness sewer

channel of coefficient (S_{nsew}= -2.12; Fig. 4h), flow path width (S_α=1.25; Fig. 4e), and retention depth of impervious areas (S_{dimp}= -1.03; Fig. 4f) have a lower impact. The plotted curves and the deterministic solution indicate that the absolute S_{nimp}

470 and S_{nsew} values for the R2 and R3 temporal rainfall distributions (deterministic solution) are lower than for the R1 distribution (Fig. 4e–f). In turn, in the case of S_α (Fig. 4e) and S_{dimp} (Fig. 4f), it was found that the absolute values of the sensitivity coefficients calculated for the R1 distribution have lower values than for R2 and R3. When the model is calibrated based on hydrographs reflecting the reaction of the analyzed catchment to normal rain (constant temporal rainfall distribution in an event - R1), the greatest effect on the Q_m in the $Q_{g,m}$ domain is exerted by n_{imp} and the lowest impact is shown by d_{imp} (in terms of

475 absolute values); this is indicated by the curves in Fig. 4f–g. In turn, a different relationship, i.e. the greatest effect of d_{imp}, α and the lowest effect of n_{imp}, was found for the R2 distribution (Fig. 4e–f). These relationships indicate a significant effect of temporal rainfall intensity distributions on the model sensitivity to changes in the coefficients calibrated in the domain of $Q_{g,m}$ values.

The results of the present analyses may be highly important in engineering practice, as they confirm that, with the Q_m values

480 assumed as the basis for calibration, the hydrograph should be selected in a way facilitating identification of the coefficients (α, d_{imp}, n_{imp}, n_{sew}) and validation, so that the values will be a result of rainfalls with similar intensity dynamics. Therefore, it should be underlined that, in the hydrograph intended for identification of model coefficients and validation, the relationship between the dependent variables and the calibrated coefficients must have a similar form.

5.4.3 Sensitivity coefficients (maximum instantaneous flow vs. size of threshold Q_m)

485 The plotted curves (probabilistic solution) with the deterministic solutions showed that the greater the rainfall intensity (rising Q_m value), the smaller the values of the sensitivity coefficients (S_α, S_{nimp}, S_{dimp}) (Fig. 4a–d). This indicates a decline in the sensitivity of the model of prediciting the probability of exceeding $Q_{g,m}$ to changes in calibrated parameters (α, n_{imp}, d_{imp}) (Fig. 4a–c). An inverse relationship was found for the n_{sew} value (Fig. 4d). During the calibration of the catchment model for normal rainfall (maximum intensity in the middle of the event – R2), the model exhibited the highest sensitivity ($Q_{g,m}$ prediction) to

490 changes in the retention of impervious areas (S_{dimp}= -2.342; Fig. 4b) and the lowest sensitivity to the Manning roughness coefficient of impervious areas (S_{nimp}= -0.683; Fig. 4c). In the case of calibration of catchment model for heavy and torrential rainfall events, the maximum instantaneous flow Q_m in the region of corresponding $Q_{g,m}$ values exhibited the highest sensitivity to changes in n_{sew} (Fig. 4d).

The relationships presented in this study have been scarcely analyzed by other researchers (Barco et al., 2008; Krebs et al.,

495 2014; Li et al., 2014) in terms of catchment outflow modeling. These relationships, which confirm the significant effect of rainfall intensity distribution on hydraulic phenomena occurring in the sewer network, were described by Jato-Espino et al. (2018) in their study of stormwater overflow. The authors showed a statistically significant effect of the rainfall intensity distribution on the relationship between stormwater overflow onto the land surface and catchment characteristics. A certain analogy with the calculation results described in the present study may be suggested. This is related to the fact that, along with

500   the increase in rainfall intensity, Jato-Espino et al. (2018) reported a decline in the sensitivity of the model to the values of selected catchment characteristics; this is equivalent to a decrease in the sensitivity of the model to the calibrated parameters.

5.4.4 Sensitivity coefficients (uncertainty of estimated coefficients in the logit model)

The calculations showed that the uncertainty of parameter estimation in logit models exerts a strong effect on the values of the sensitivity coefficients calculated for the analyzed cases. This is confirmed by the determined range of variability of the
505   sensitivity coefficient values (S_α, S_{nimp}, S_{dimp}, S_{nsew}) depending on the size of the respective percentiles (Fig. 4 – 5). In most of the calculation variants (with the exception of α; Fig. 4a, 4e, 5a), the difference between the determined values of the sensitivity coefficients (for the different temporal rainfall distributions R1, R2, R3 and rainfall genesis - normal, heavy, and torrential rains) was shown to decrease with the increase in the percentile values.

Different relationships were observed in the analysis of the variability of S_{xi} values shown in Fig. 5a. In this case, for percentiles
510   below 0.36, the highest and the lowest S_α values were obtained for $V(Q_{m,g}=2.50 \text{ m}^3/\text{s})$ and $V(Q_{m,g}=0.30 \text{ m}^3/\text{s})$, respectively. The analysis of the effect of rainfall distribution (R1, R2, R3) on the model sensitivity (calibrated Q_m value) revealed an increase in the difference in the sensitivity coefficient S_α values with the increase in the percentiles. As shown by the analysis of the values of sensitivity coefficients S_α and S_{dimp} (Fig. 4a, 4b), the relationship $S_{\alpha(dimp)}(Q_m=0.75 \text{ m}^3/\text{s}) > S_{\alpha(dimp)}(Q_m=2.50 \text{ m}^3/\text{s})$ was obtained for percentile values above 0.42, whereas an inverse relationship was found for lower percentile values.

515   6 Summary and conclusions

Modeling of outflows and calibration of hydrodynamic models with design of tools supporting this task represent a relevant current research topic. It is necessary to search for methods that will yield reliable results reflecting the reality as well as possible on the one hand. On the other hand, with their acceptable time- and cost-efficiency in retrieval and analysis of data, the methods should have the potential to be used in practice by a wide group of engineers. This study has shown that the
520   logistic regression model can be used for analyses of the sensitivity of the maximum flow in a hydrograph and hydrograph volume in a rainfall event. The hydrograph parameters depended on the temporal rainfall intensity distribution in the rainfall event and parameters identified in the SWMM model. In addition to their scientific aspects, the proposed logit models may be a useful tool for forecasting the variability of the parameters of catchment outflow hydrographs, which confirms the usefulness of the developed tool.

525   The sensitivity coefficient proposed in the study facilitates determination of the impact of selected parameters of the SWMM model on the outflow hydrograph parameters with consideration of rainfall genesis and variability of temporal rainfall distribution in a rainfall event. Furthermore, it has been demonstrated that the rainfall genesis and the temporal variability of rainfall intensity in a rainfall event should be included in the selection of hydrographs for calibration and validation of the model. It was found that the higher the rainfall intensity determining the modeled outflow hydrograph, the lower the sensitivity
530   of the identified SWMM model parameters to the maximum outflow and hydrograph volume. The calculations have indicated

that the uncertainty of the coefficients identified in the logit model has a significant impact on the determined sensitivity coefficients. The aspects discussed above are highly important for the procedure of hydrodynamic model calibration, which ultimately has a significant effect on the accuracy of identified model parameters.

Given the usefulness of the presented calculation results, further investigations are recommended to verify the logit models
535   and relationships presented in this study. There is also a need for analyses of other urban catchments with different physical and geographical characteristics, which may contribute to development of a universal model.

7 Appendices

Appendix A: List of Symbols

t_r – rainfall duration,

540   P_{tot} – rainfall depth,

α_j – estimated coefficient of logistic regression model,

α_0 – rainfall efficiency coefficients taking into account the normal, heavy, and torrential rain types,

q_u – hydrograph caused by normal rainfall (according to the Chomicz scale),

q_s – hydrograph caused by heavy rainfall (according to the Chomicz scale),

545   q_g – hydrograph caused by torrential rainfall (according to the Chomicz scale),

R1, R2, R3, R4 - temporal of rainfall distribution,

V – volume of hydrograph,

Q_m – maximum instantanous flow,

V_g – threshold of volume of hydrograph,

550     $Q_{g,m}$ – threshold of maximum instantanous flow,

ξ – function describing the temporal intensity distribution,

n_{imp} – Manning roughness coefficient for impervious areas,

n_{sew} – Manning roughness coefficient for sewer channels,

α – coefficient for flow path width,

555   GLUE – Generalized Likelihood Uncertainty Estimation,

d_{imp} – retention depth of impervious areas,

S_{xj} – sensitivity coefficient,

p – probability of exceeding of $Q_{g,m}$ and V_g,

SWMM – Storm Water Management Model,

560   SPEC – Specificity,

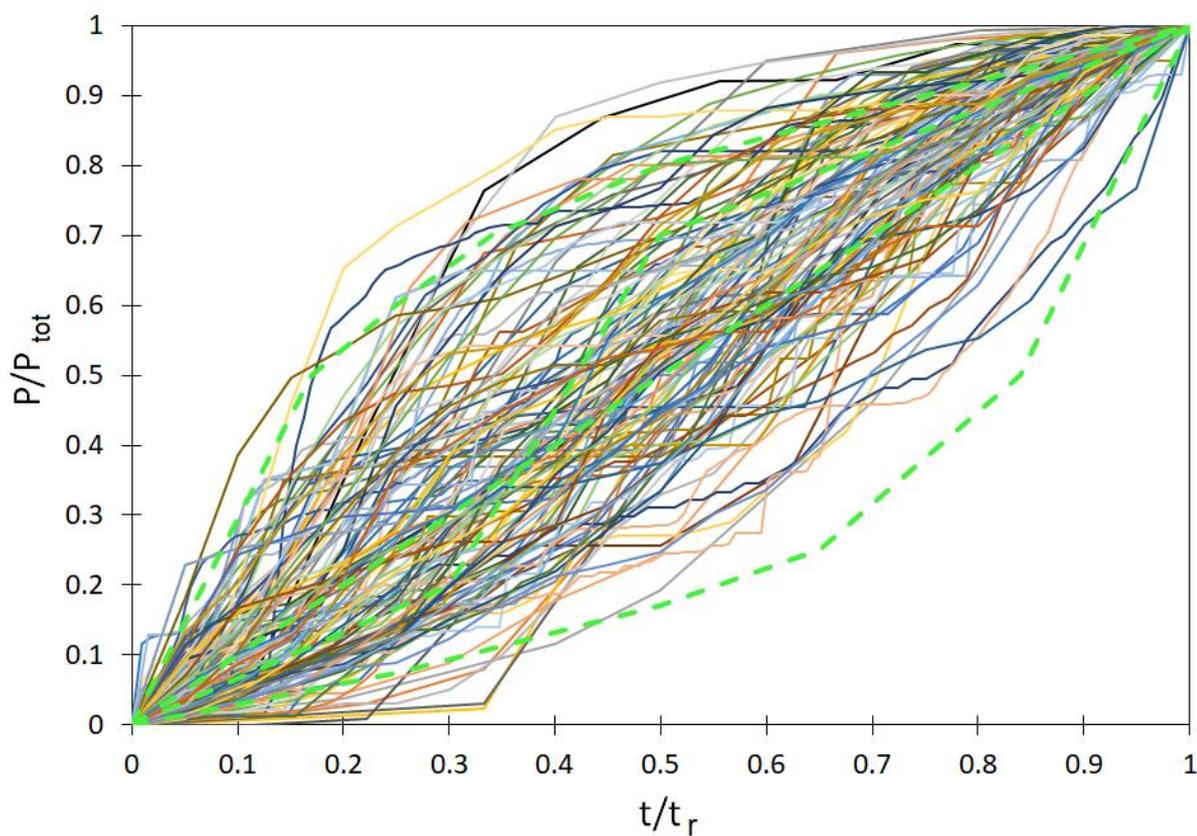
SENS – Sensitivilty,

R_z^2 – calculation error,

ε – empirical coefficient for conversion of the Q_m^* value into p^*,

Q(t) – outflows from of the catchment at time t,

565     $x_{1, 2, j=n}$ – calibrated parameters in the SWMM model,

Appendix B: Supporting graphical information

570   **Figure B1. Dimensionless rainfall curves $P/P_{tot}=f(t/t_r)$ obtained from measurements performed in 2008–2016.**

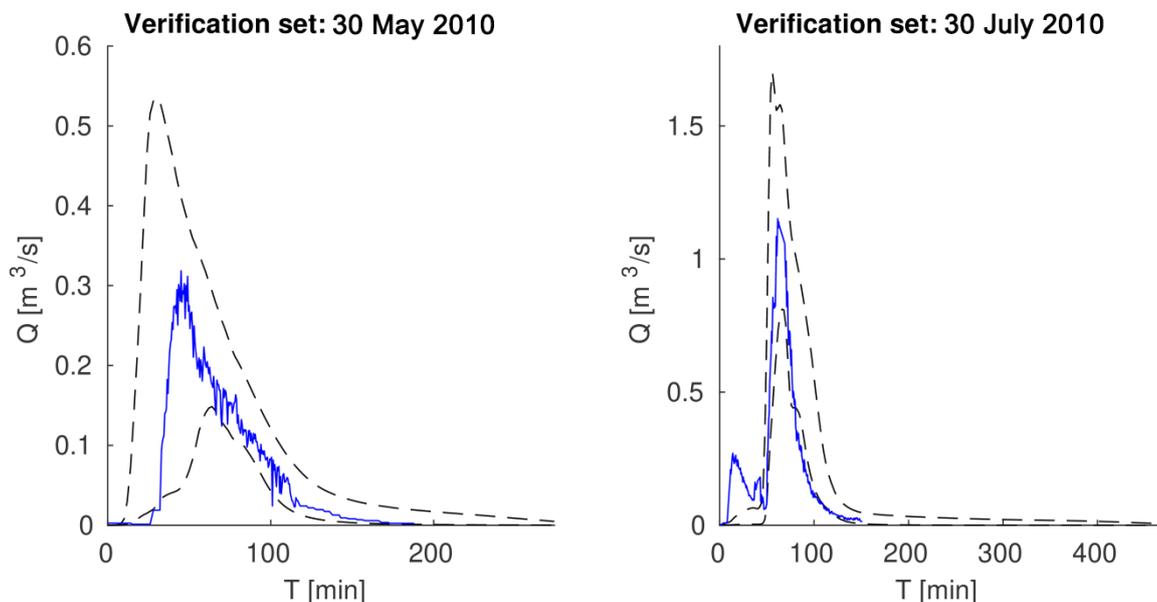



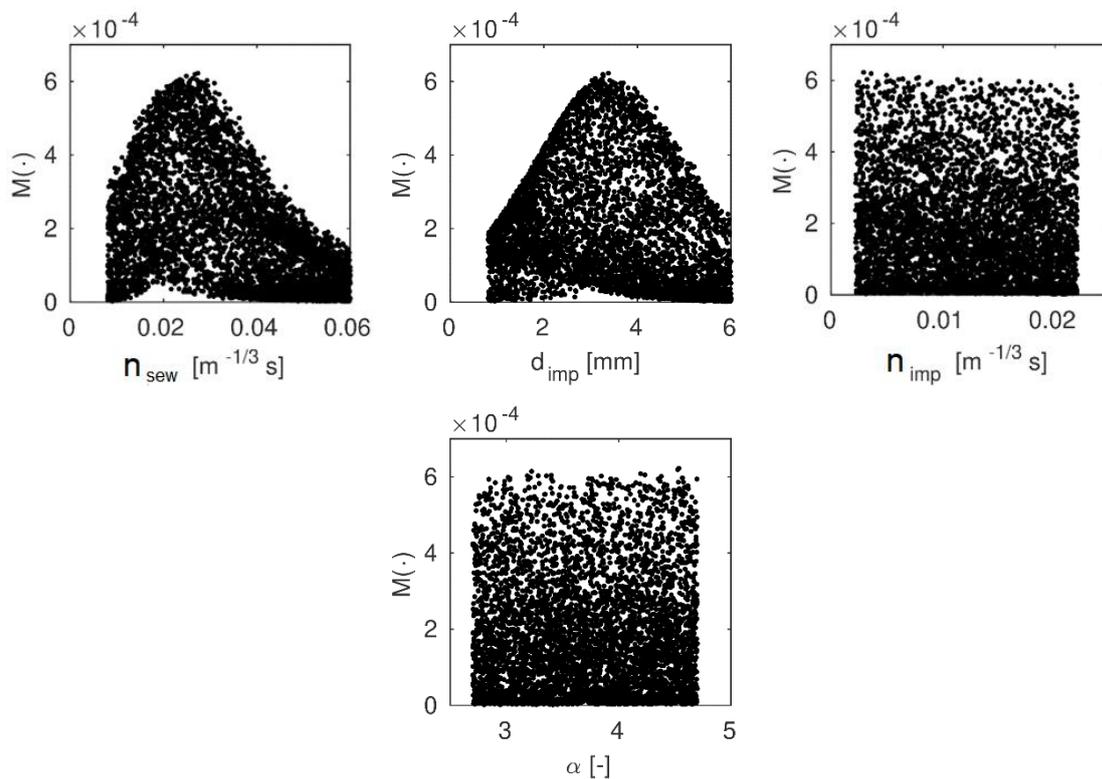
Figure B2. Comparison of measurement results of hydrograms of outflow from the catchment area with GLUE calculations.

575

Figure B3. Calculated likelihood function - scatter plots of M values versus calibrated catchment parameters in SWMM.

Code availability: The authors announce that there is no problem for sharing the used model and codes by make request to
580 corresponding author.

Data availibility: The authors confirm that data supporting the findings of this study are available from the corresponding
author by request.

585 **Author contribution:** Conceptualization: Szeląg, Methodology: Fatone, Szeląg, Kiczko, Majerek; Formal analysis and
investigation: Fatone, Szeląg, Kiczko, Majerek, Łagód, Majewska; Writing - original draft preparation: Szeląg, Kiczko,
Majerek, Łagód; Writing - review and editing: Fatone, Szeląg, Majerek, Łagód, Drewnowski; Supervision: Fatone, Szeląg,
Łagód.

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