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Extended Evaluation of the Impact of Rainfall, Sewer Network and Land Use Retention on Drainage System Performance in a Multi-Criteria Approach – Modeling, Sensitivity Analysis

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ABSTRACT

An extensive methodology for analyzing the impact of catchment and sewer network retention on drainage system operating conditions during hydraulic overloading is presented. To evaluate the performance of the sewer system and identify the need for repair actions, logistic regression models were developed to predict the unit flooding volume and manhole overflowing. An advanced sensitivity analysis was performed to determine the key parameters (retention and roughness of impervious and pervious areas as well as sewer channel retention) conditioning the reduction of uncertainty in the simulation results and ensuring the assumed hydraulic effect. A coefficient expressing the quotient of the duration of rainfall conditioning the exceedance of the limits of the unit flooding volume (13 $m^3 \cdot ha^{-1}$) as well as the degree of overflowed manholes (0.32) was determined, allowing the determination of the key performance criterion of the sewer network to take corrective action depending on field and channel retention. It was shown that the catchment area retention had the key influence on the conditions of sewer operation and the probability of remedial work. Increasing the rainfall duration led to a decrease in sensitivity coefficients with respect to the identified parameters of the SWMM model, which is important when selecting rainfall events for the calibration and validation sets. The usefulness of the developed methodology was demonstrated at the stage of building mechanistic models, which is of significance when planning field studies.

Keywords: stormwater system, environmental impact, multi-criteria approach, modelling, SWMM, GLUE, sensitivity analysis.

INTRODUCTION

Climate change, ongoing urbanization, and reduced pipe throughput contribute to the deterioration of receiving waters, resulting in an increased frequency and volume of stormwater flooding events in urban catchments [1, 2, 3]. To mitigate these impacts on the environment and living standards, decision-makers need to modernize stormwater networks through the implementation of green infrastructure or pipe retention systems [4, 5]. Ensuring optimal solutions, including hydraulic effects, requires adherence to stormwater network operation standards defined by the European Standard EN 752 [6]. This standard determines the total number of stormwater flooding events within the assumed period [7, 8, 9]. Additionally, quantitative criteria, expressing the depth of stormwater [10], i.e. determining the unit flooding volume per paved area of catchment (referred to as specific flood volume) and specifying the degree of overflowed manholes in the stormwater network (referred to as degree of flooding) were introduced [11].

Depending on the available criteria, modeling can be performed using different computational tools [12, 13, 14, 15]. Mechanistic models (MCM) are usually applied for this purpose, enabling the modeling of hydraulic conditions in a stormwater network, as well as the depth and area of flooding [16, 17]. This usually requires integrating the hydraulic model with the digital terrain model (DTM) [18, 19]. If data are unavailable, simplified solutions can be used, modeling the volume of stormwater flooding for individual manholes. One of the most commonly used simplified approaches is SWMM (Storm Water Management Model) [18, 20]. The prediction of flooding is a complex issue resulting from the interaction of land use, surface runoff, channel flow, and hydraulic characteristics of manholes [21, 22, 23]. To account for the above factors, a number of coefficients are included in the mechanistic models, which require calibration [24, 25]. This leads to over-parameterization of MCM models, resulting in problems with the identification of calibrated parameters [26, 27]. The strong interaction between parameters, the limited number of inputs to developed MCM models, the simplified de-parameterization of land use, as well as the layout of the sewer network lead to problems with model calibration and influence the uncertainty of predictions [25, 28].

Sensitivity analysis constitutes an approach to reduce the number of calibrated parameters [29, 30, 31], especially integrated with uncertainty analysis. This approach is often used during the implementation of optimization methods for the parameter identification. A literature review [32, 33] indicates that sensitivity analysis is also carried out by global and local methods, which do not take into account any influence of local rainfall conditions and the variability of identified parameters on the simulation results.

MCM models enable prediction of continuous values (flood volume, number of flooded manholes), but prevent prediction of the need to undertake repair action [25]. This limitation can result in problems with planning field studies during the development step of MCM models to be used for catchment management. Currently, there is a lack of guidelines for selecting rainfall events for the calibration and validation set [27], which has a major impact on the fitting of predictions to measurements and the reliability of the resulting predictions as a basis for making decisions on corrective actions [34].

This study presents the possibility of implementing the given computational methodology with respect to proposed parameters, such as specific flood volume and the degree of flooding, as the operating criteria for stormwater networks. A logistic regression model already applied for simulating stormwater network operation was used for this purpose [35]; however, its use in the applied approach constitutes a novel application. Moreover, in terms of specific flood volume and degree of flooding, an innovative analysis has been proposed that involves the development of a sensitivity coefficient of the hydrodynamic model. This enables the effect of (i) the influence of rainfall intensity, (ii) the frequency of its occurrence, and (iii) the parameters to be identified. So far, this aspect has not been considered in the proposed catchment model and calibration procedures to determine operational parameters.

STUDY AREA

The investigated urban catchment is located in the city of Kielce, Poland (Eastern Europe). Kielce is found in the Świętokrzyskie Region with an average population density of about 107 persons·km^{-2} [25]. The studied catchment is positioned in the southeastern part of the city and is occupied with housing estates, public utility buildings, and the main streets. The impervious areas in the catchment constitute 40%, whereas the remaining part is pervious. It was determined that the retention of the impervious areas amounts to 2.5 mm, whereas that of pervious areas is equal to 6.0 mm [9]. The road network density in the analyzed area amounts to 108 m·ha^{-1}. The elevation of the highest point of the catchment is 271.20 m a.s.l., whereas that of the lowest one is 260.0 m a.s.l. In the considered catchment, the total length of the stormwater network amounts to 5584 m, including the main pipe, which has a length of 1569 m. The diameter of the main pipe ranges from 600 to 1250 mm, whereas the diameters of the side pipes range from 300 to 1000 mm. The slopes of the pipes are within the range of 0.04 to 3.90% [25].

The catchment area under study is depicted in Figure 1. The map shows the catchment boundaries, as well as the main sewer and side channels. The stormwater from the catchment flows into a diversion chamber (DC); up to a depth of 0.42 m, the entire volume of stormwater is directed to a stormwater treatment plant (STP). The treated stormwater is discharged to the Silnica River. If, due to intense rainfall, the level of stormwater in the DC exceeds 0.42 m, it is discharged through an overflow structure (OV) into the Silnica River. A MES-1 flow meter was installed ca. 3 m from the diversion chamber inlet to measure and record the flow every minute during intense rainfall events. Location of devices is shown in Figure 1.

Based on data spanning 2010–2020, it was observed that MES-1 flow meter recorded flows ranging from 1 to 9 $dm^3 \cdot s^{-1}$ during dry periods, suggesting infiltration. The flow meter's probe gauges water level (via water level pressure measurement) and average flow rate of stormwater (utilizing the Doppler effect). These measurements, combined with the specific shape and dimensions of the canal, enable the built-in microprocessor to calculate the volumetric flow rate of stormwater. A rainfall station, conducting continuous rainfall measurements since 2008 at a 1 – minute resolution, is located 2.5 km away from the catchment border.

RESEARCH METHODOLOGY

In this section the innovative and multicriteria methodology is presented, mainly based on the operational evaluation of stormwater networks (Figure 2). It considers two criteria, including:

- specific flood volume, determining the unit flooding volume per 1 ha of the catchment:

$$\lambda_1 = \frac{\sum_{i=1}^{K} V_{t(i)}}{A_{imp}} \tag{1}$$

where: V_t is the volume of stormwater flooding from the i-th manhole, K is the number of manholes in the stormwater network, and A_{imp} is the impervious area,

- degree of flooding, i.e. the degree of overflowed manholes in the stormwater network:

$$\lambda_2 = \frac{\sum_{i=1}^{K} N_{K,f}}{K} \tag{2}$$

where: $\Sigma N_{K,f}$ – the number of overflowed manholes in the stormwater network.

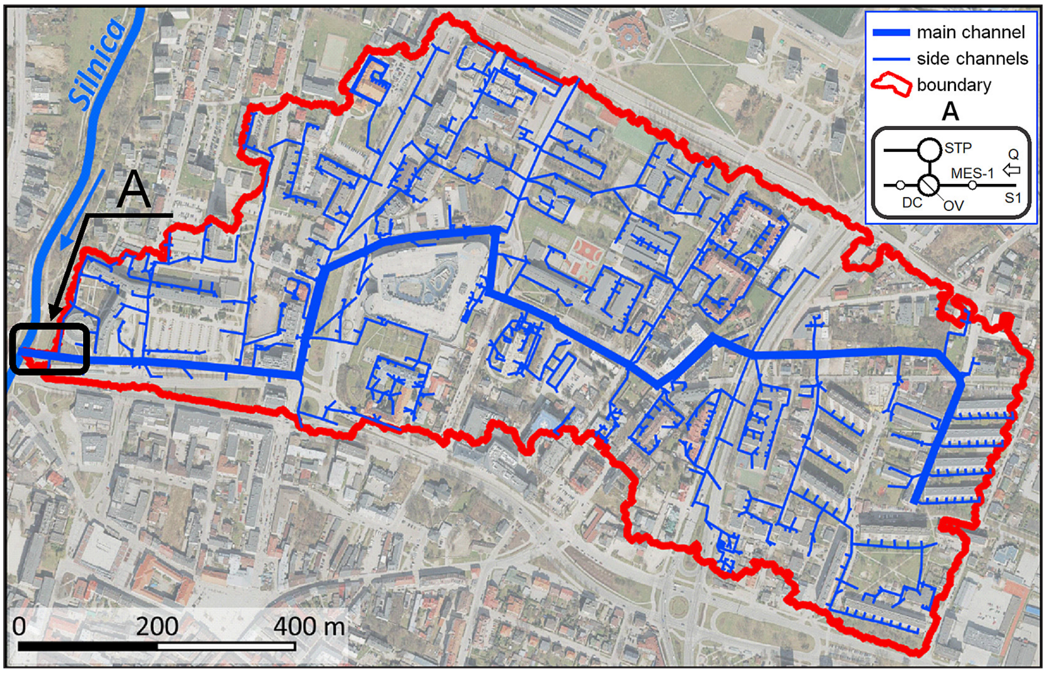

Figure 1. Investigated catchment in Kielce, Poland. MES-1 – flow meter, OV – overflow structure, DC – diversion chamber, STP – stormwater treatment plant

According to Siekmann and Pinnekamp [11], a stormwater network requires urgent modernization for the values of $\lambda_1 > 13$ m^3·ha^{-1} and values of $\lambda_2 > 0.32$. The maximum values of λ_1 and λ_2 presented above constituted the basis for developing the logistic regression models. Such parameters are the most important in decision making regarding the repair action of existing systems. The proposed computation algorithm consists of 6 modules (Figure 2). The development of algorithm includes four steps:

- Modules 1, 2 – collecting the data and developing of mechanistic model,
- Module 3 – uncertainty analysis with GLUE method,
- Modules 4, 5 – development of a logistic regression model to assess the relationship between specific flood volume and degree of flooding with sensitivity analysis,
- Module 6 – analysis of the dependence of the duration of rainfall that results in exceeding the thresholds of specific flood volume and degree of flooding.

Separation of independent rainfall events (DWA-A118)

In the analysis the independent rainfall events (with uniformed distribution) for modeling of stormwater network operation were separated, based on continuous rainfall time series (2010–2019). On the basis of the performed analysis of the rainfall data, it was observed that the number of rainfall events in any year ranged from 12 to 30 (202 rainfall events), in which the rainfall depths were in the range of P_t = 5.2–80.2 mm, the maximum 30 – minute rainfall depths in a rainfall event in any year were equal to $P_{t=30}$ = 2.5–41.2 mm, the rainfall durations were t_r = 15–150 min and the dry period was t_{rd} = 6–336 h. Since the uncertainty of the SWMM parameters is included in the calculations, the selection of rainfall events for modeling of operation of the stormwater network is not a simple task. The detailed methodology is discussed by Szeląg et al. [25].

Rainfall frequency was established by considering rainfall characteristics such as depth and duration, utilizing the regional model for Poland introduced by Bogdanowicz and Stachy [36].

Mechanistic model of the catchment (SWMM)

Modeling of the investigated catchment was performed using a calibrated mechanistic model developed in SWMM. The analyses were based on a mechanistic model with an area of 62 ha, comprising 92 subcatchments with areas ranging from 0.12 ha to 2.10 ha (as shown in Figure 1), whereas the imperviousness equaled 5–90%. The considered model consists of 72 pipes and 82 manholes. During calibration, it was determined that the retention depth of the impervious areas D_{imp} = 2.50 mm, pervious areas D_{per} = 6.0 mm, Manning roughness coefficients of impervious and pervious areas were n_{imp} = 0.025 m$^{-1/3}$·s and n_{per} = 0.10 m$^{-1/3}$·s. The width of the run-off path was determined based on the dependence $W = \omega \cdot A^{0.50}$, where ω = 1.35. The considered catchment model constituted the basis for the analyses related to the quantity and quality of stormwater, tank dimensioning, and operation of the stormwater overflow structure [9, 25].

In the applied approach, the stormwater operational parameters (specific flood volume, degree of flooding) were predicted using the "Flooding"

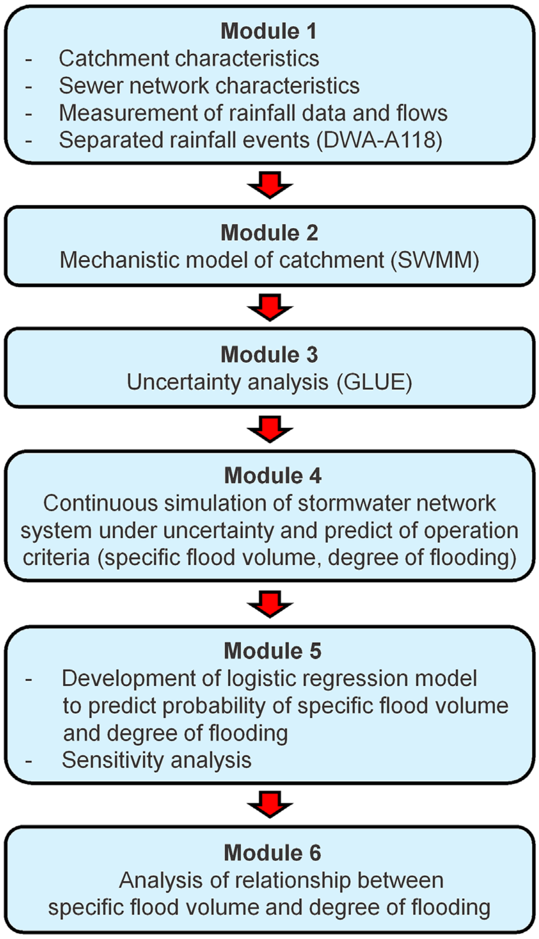

Figure 2. Calculation algorithm of the methodology for analyzing the operation of a stormwater network in the context of the specific flood volume and the degree of flooding

option for a single junction, which enables a reduction in the quantity of measurement data required [9].

Uncertainty analysis (GLUE) methodology

In this paper, the generalized likelihood uncertainty estimation (GLUE) method was used for uncertainty analysis. The theoretical basis of the method is discussed in detail in the studies by Beven and Binley [37] and Romanowicz and Beven [38]. In the GLUE method, the basis for the identification of parameter distributions was Bayesian estimation, in which for the assumed a priori parameter distributions the so called a posteriori distributions were determined by the likelihood function. The following parameters (uniform distribution) were included in the SWMM model: coefficient for flow path width (α), retention depth of impervious areas (D_{imp}), retention depth of pervious areas (D_{per}), Manning's roughness coefficient for impervious areas (n_{imp}), Manning's roughness coefficient for pervious areas (n_{per}), Manning's roughness coefficient of sewer channels (n_{sew}), correction coefficient for subcatchments slope (γ) and correction coefficient for percentage of impervious areas (β). Details on the parameters used are provided by Kiczko et al. [39] and Szeląg et al. [40].

Measures of goodness of fit of the results and a posteriori distributions were calculated based on simulations performed for the observed hyetograms and hydrograms. For both events utilized in parameter identification (15 September 2010 – P_t = 9.2 mm, t_r = 286 min, and 8 July 2011 – P_t = 8.2 mm, t_r = 60 min), 96% of observed points were encompassed by the confidence bands. In the validation sets 89% of observed points fell within the bands for the May 30, 2010 event (P_t = 12.5 mm, t_r = 107 min), and 60% for the July 30, 2010 event (P_t = 16.5 mm, t_r = 270 min).

Continuous simulation of stormwater systems

Based on the separated (M = 200) rainfall events for the catchment area, the operation of the stormwater drainage network was simulated by determining the volume of flooding for each i-th manhole and the number of overflowed manholes. There were 5000 simulations of SWMM parameters combinations – a priori distribution (Section: Uncertainty analysis (GLUE) methodology) of independent rainfall events, for which λ_1 and λ_2 were determined. The data obtained was used to develop a logit model, with 80% of the data used for training, 10% for testing, and the other 10% for validation. To simulate the stormwater network operation, regarding the logistic regression models, rainfall events for which the rainfall depth P_t > 5.0 mm were selected. It resulted in the rainfall duration in the range 10–135 minutes.

Logistic regression model to predict the probability of the operation criteria

The logit model describes the following general dependence:

$$p = \frac{\exp(\alpha_0 + \alpha_1 \cdot x_1 + \alpha_2 \cdot x_2 + \alpha_3 \cdot x_3 + \cdots + \alpha_i \cdot x_i)}{1 + \exp(\alpha_0 + \alpha_1 \cdot x_1 + \alpha_2 \cdot x_2 + \alpha_3 \cdot x_3 + \cdots + \alpha_i \cdot x_i)} = \frac{exp(X)}{1 + exp(X)} \quad (3)$$

where: p – probability of exceeding the maximum value of the specific flood volume (λ_1) and the degree of flooding (λ_2); α_0 – absolute term; α_1, α_2, α_3, α_i – values of coefficients estimated with the maximum likelihood method, X – vector describing the linear combination of the independent variables; x_i – independent variables describing rainfall characteristics, e.g., rainfall depth, its duration, and the parameters calibrated in the SWMM. Identification of independent variables was performed using a stepwise algorithm that also eliminates correlated independent variables [41].

In the performed analyses, identification of the data obtained from the SWMM simulation to the binary form was based on the following criteria:

a) when $\lambda_1 \geq 13$ m^3·ha^{-1}, then 1, in the remaining cases 0,
b) when $\lambda_2 \geq 0.32$, then 1, in the remaining cases 0.

Following literature findings [11], values $\lambda_1 \geq$ 13 m^3·ha^{-1} and $\lambda_2 \geq 0.32$ correspond to $p \geq 0.5$. Specificity (SPEC), sensitivity (SENS) and accuracy (ACC) were used to assess the goodness of fit between predictions and measurements.

Sensitivity analysis

In the performed investigations, the analysis of model sensitivity was carried out using local sensitivity analysis [24, 42, 43]. In the proposed solution the sensitivity coefficient was defined, described by the following Equation:

$$x_j = \frac{\partial p}{\partial x_i}\cdot\frac{x_i}{p} = \frac{p(x_{i,g}+\Delta x_i) - p(x_{i,g};\,\lambda)}{(x_{i,g}+\Delta x_i) - x_{g,i}}\cdot\frac{x_i}{p(x_{i,g};\,\lambda)} = \alpha_i\cdot x_i\cdot\left(1 - p(x_{i,g};\,\lambda)\right) \tag{4}$$

where: x_i – values of independent variables, λ – values of λ_1 and λ_2 parameters which constitute the basis for assessing the operation of the stormwater network, $p(x_{i,g} + \Delta x_i)$ – probability of exceeding $\lambda_1(\lambda_2)$ for the value $(x_{i,g} + \Delta x_i)$, $p(x_{i,g}, \lambda)$ – probability of exceeding the value $\lambda_1(\lambda_2)$ for the set of independent variables involving rainfall characteristics and calibrated SWMM parameters. The individual steps for calculating the sensitivity coefficients according to Equation 4 are given in Szeląg et al. [40]. On the basis of Equation 4, sensitivity coefficients were calculated for the calibrated SWMM parameters using the models to predict the probability of specific flood volume and degree of flooding in the stormwater network. These calculations were done for t_r = 15–135 min and C = 3, 5 assuming the SWMM parameters were determined from calibration [39].

Relationship between the specific flood volume and degree of flooding

Based on literature review [9, 11], it can be concluded that the probability of a specific flood volume (λ_1) and a degree of flooding (λ_2) depends on the rainfall data (rainfall depth and duration) and the parameters calibrated, used in SWMM (D_{imp}, D_{per}, n_{imp}, n_{per}, n_{sew}, α, β, γ, etc.). It was assumed, following Siekmann and Pinnekamp [11], that when the value of λ_1 = 13 $m^3\cdot ha^{-1}$ or λ_2 = 0.32, then the stormwater network requires repair action and the calculated values of the probability of a specific flood volume and the probability of a degree of flooding are equal to 0.5. For p = 0.50, by appropriately transforming Equation 3, it can be written that X = 0 (where X – linear combination of independent variables included in logistic regression models). For the above assumptions, the ratio of rainfall durations for which λ_1 = 13 $m^3\cdot ha^{-1}$ and λ_2 = 0.32 can be written with an Equation of the form:

where: κ – coefficient in the form of $t_{r2}(\lambda_2)\cdot t_{r1}(\lambda_1)^{-1}$, which describes the relative difference between the duration of rainfall for which λ_1 = 13 $m^3\cdot ha^{-1}$ or λ_2 = 0.32; α_0^1, α_1^1, α_2^1, α_3^1, α_4^1, α_5^1, α_6^1, α_7^1, α_8^1, α_9^1, α_{10}^1 – coefficients estimated by the method of maximum likelihood in the logit model for predicting specific flood volume; α_0^2, α_1^2, α_2^2, α_3^2, α_4^2, α_5^2, α_6^2, α_7^2, α_8^2, α_9^2, α_{10}^2 – coefficients estimated by the method of maximum likelihood in the logit model for predicting degree of flooding.

RESULTS AND DISCUSSION

Uncertainty analysis (GLUE)

Calculations of the stormwater network operation in the considered catchment accounting for uncertainty showed that the median values of the specific flood volume (λ_1) in the range t_r = 30–135 min for return period C = 2, 3 and 5 were 19–24 $m^3\cdot ha^{-1}$, 36–44 $m^3\cdot ha^{-1}$ and 53–70 $m^3\cdot ha^{-1}$. The λ_1 values for t_r = 30 min and for C values of 2, 3, and 5 within the 95% confidence interval varied within the ranges 8–42 $m^3\cdot ha^{-1}$, 21–67 $m^3\cdot ha^{-1}$ and 40–90 $m^3\cdot ha^{-1}$ [9]. The median values of the degree of flooding (λ_2) for t_r = 30–135 min and for C values of 2, 3, and 5 were 0.10–0.65, 0.64–0.87 and 0.87–0.93. The situation is shown in Figure 3.

Determination of the logistic regression model to predict the probability of the specific flood volume and the degree of flooding

The ROC AUC scores obtained for λ_1 and λ_2 were 0.987 and 0.996, respectively. The coefficients (α_i) determined in the models (using forward stepwise algorithm), testing probability (p_{test}), standard deviation (S.dev) and measures of fit (SENS and SPEC) for the training, testing, and validation sets are presented in Table 1. Based on the data in Table 1, it can be determined that among the independent variables including rainfall characteristics and parameters calibrated in the SWMM (β, n_{sew}, D_{imp}, n_{imp}, α), only n_{per} has no

$$\kappa = \frac{\alpha_0^1-\alpha_0^2+(\alpha_1^1-\alpha_1^2)\cdot C+\alpha_2^1\cdot t_r+(\alpha_3^1-\alpha_3^2)\cdot D_{imp}+(\alpha_4^1-\alpha_4^2)\cdot D_{per}+(\alpha_5^1-\alpha_5^2)\cdot n_{imp}}{\alpha_2^2\cdot t_r} + \frac{(\alpha_6^1-\alpha_6^2)\cdot n_{per}+(\alpha_7^1-\alpha_7^2)\cdot n_{sew}+(\alpha_8^1-\alpha_8^2)\cdot\alpha+(\alpha_9^1-\alpha_9^2)\cdot\beta+(\alpha_{10}^1-\alpha_{10}^2)\cdot\gamma}{\alpha_2^2\cdot t_r} \tag{5}$$

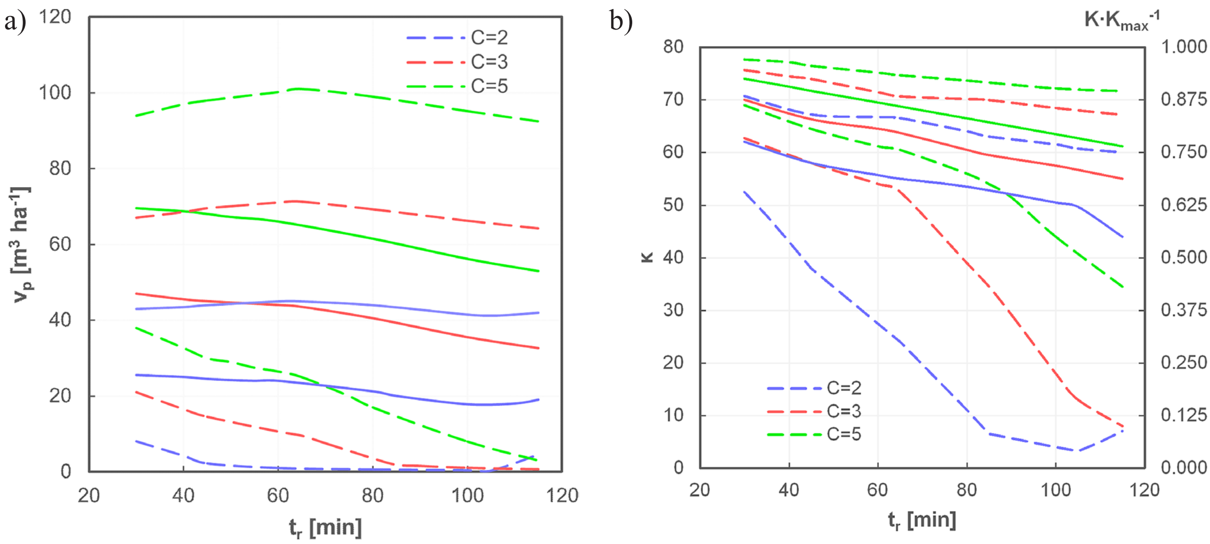

Figure 3. The rainfall duration (tr) and its frequency (C) effect on sewer performance measures: (a) λ_1, (b) λ_2 accounting for the model uncertainty

Table 1. Values of the coefficients in the developed logit model and measures of fit between the results of calculations and measurements

Variables	$\lambda_1 \geq 13\ m^3 \cdot ha^{-1}$			$\lambda_2 \geq 0.32$		
	Value	S. dev	p_{test}	Value	S. dev	p_{test}
Intercept	**-24.150**	0.420	< 0.001	**-21.222**	0.44	< 0.001
C	**3.743**	0.043	< 0.001	**4.33**	0.089	< 0.001
t_r	**-0.061**	0.001	< 0.001	**-0.152**	0.003	< 0.001
α	**0.860**	0.033	< 0.001	**0.841**	0.056	< 0.001
n_{imp}	**-247.016**	3.960	< 0.001	**-225.47**	6.591	< 0.001
n_{per}	-1.242	1.531	< 0.424	1.023	2.672	< 0.702
D_{imp}	**-0.546**	0.016	< 0.001	**-0.206**	0.027	< 0.001
D_{per}	**-0.129**	0.011	< 0.001	**-0.054**	0.018	0.003
β	**12.241**	0.160	< 0.001	**16.729**	0.338	< 0.001
γ	**1.430**	0.105	< 0.001	**1.458**	0.179	< 0.001
n_{sew}	**408.920**	4.366	< 0.001	**568.55**	10.568	< 0.001
Train	SENS = 96.56%; SPEC = 97.86% Acc = 95.92%			SENS = 94.48%; SPEC = 99.51% Acc = 98.76%		
Test	SENS = 95.15%; SPEC = 93.10% Acc = 92.15%			SENS = 95.48%; SPEC = 93.51% Acc = 94.06%		
Validation	SENS = 95.23%; SPEC = 93.34% Acc = 94.36%			SENS = 95.30%; SPEC = 91.20% Acc = 92.12%		

Note: variables in bold are statistically significant.

statistically significant influence (for the assumed significance level of 0.05) on the calculation results of the probability of specific flood volume and probability of degree of flooding. Simultaneously, while analyzing the data in Table 1, it was noted that the developed logit models were characterized by high prediction. This is confirmed by sufficiently high values of SENS > 94%, SPEC > 93% and Acc > 92% for the training, testing, and validation sets, respectively.

Sensitivity analysis

The influence of the return period (assumed as C = 3, and 5), rainfall duration (t_r = 15–135 min) and the parameters calibrated in the SWMM on the sensitivity of the model for $p_{\lambda 1}$ and $p_{\lambda 2}$ prediction was determined. The sensitivity coefficients for the calibrated SWMM parameters (α, β, γ, D_{imp}, D_{per}, n_{imp}, n_{sew}) with respect to the models for the $p_{\lambda 1}$ and $p_{\lambda 2}$ calculations are shown

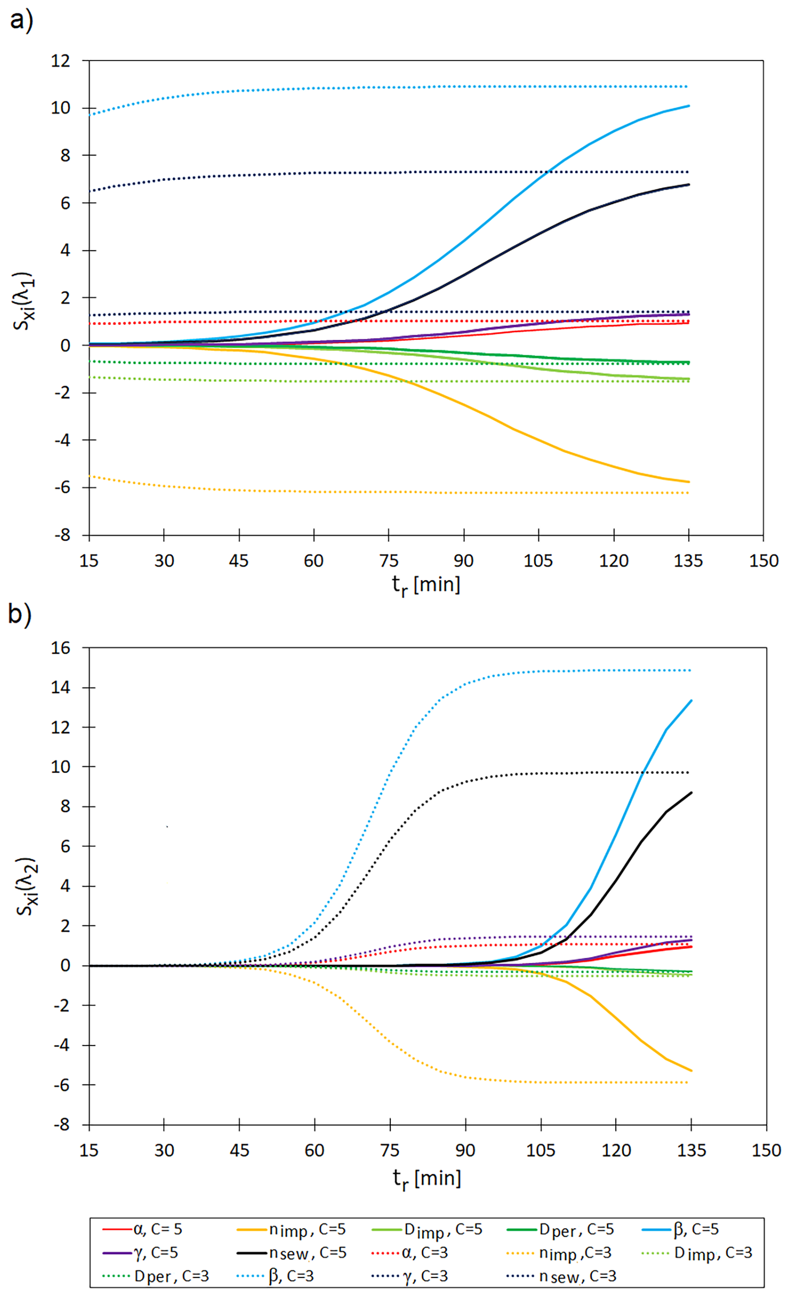

Figure 4. Influence of the rainfall duration (tr) and return period (C) on the sensitivity coefficient: a) $S(\lambda_1)x_i$, b) $S(\lambda_2)x_i$ for the values of SWMM parameters (x_i: α, β, γ, n_{imp}, D_{imp}, D_{per}, n_{sew})

in Figure 4a and 4b. It was demonstrated that for t_r = 15–135 min and C = 3–5, the correction coefficient for the percentage of impervious areas, Manning's roughness coefficient for impervious areas and the Manning's roughness coefficient of sewer had a key influence on the specific flood volume and the degree of flooding (Figure 4). The curves obtained and the range of variation in the sensitivity coefficients indicate that the other parameters of the SWMM model describing catchment retention (retention depth of impervious and pervious areas, width of the runoff path, average longitudinal slope of the catchment) are less important. It was shown that increasing the duration of rainfall for C = 3, and 5 led to an increase in the sensitivity coefficients with respect to the calibrated SWMM parameters, and thus the models simulating the specific flood volume (λ_1) and the degree of flooding (λ_2). While analyzing the course of the obtained curves (Figure 4a and 4b) for C = 3, and 5, it was found that the maximum values of the sensitivity coefficients (S_β, S_α, S_γ, S_{nimp}, S_{dimp}, S_{nsew}) were obtained for t_r = 105 min. For example, for t_r = 30 min and C = 5, the sensitivity coefficient $S_\beta(\lambda_1) = 0.10$, while for t_r = 75 min, $S_\beta(\lambda_1) = 2.24$ was obtained. For t_r = 30 min and C = 5, the sensitivity coefficient $S_\beta(\lambda_2) = 0.01$, and for t_r = 75 min, $S_\beta(\lambda_2) = 9.71$. It was found that increasing the return period (C) and average rainfall intensity led to a decrease in the sensitivity coefficient $S_{xi,}$ showing the influence of calibrated SWMM parameters on the $p_{\lambda1}$ and $p_{\lambda2}$ values. For C = 3, the influence of rainfall duration for t_r = 15–45 min on the calculation of S_{xi} with respect to the value of $p_{\lambda1}$ is shown in Figure 4a. The results of the calculations performed for the probability of the degree of flooding and C = 3 showed a negligible influence of the rainfall duration on the sensitivity coefficients for t_r > 105 min with respect to the identified SWMM parameters (Figure 4b).

Determination of the relation between the degree of flooding depending on SWMM parameters

Based on Equation 5, the quotients of the rainfall duration (C = 5) determining the probability of the specific flood volume and the degree of flooding equal to $p_{\lambda1} = p_{\lambda2} = 0.50$, which is equivalent to $\lambda_1 = 13$ m^3·ha^{-1} and $\lambda_2 = 0.32$, were determined. Calculations were done for the values β = 0.8–1.0, D_{imp} = 1.0–4.0 mm, n_{imp} = 0.013–0.030 m$^{-1/3}$·s and n_{sew} = 0.013–0.025 m$^{-1/3}$·s. The results of the analyses are presented in Figure 5.

It was found that the values of the degree of flooding in the stormwater network (λ_2 = 0.32) were obtained for longer rainfall durations than those conditioning the specific flood volume at λ_1 = 13 m^3·ha^{-1}. This was confirmed by the calculated values of $\kappa = t_{r2} \cdot t_{r1}^{-1}$ (Figure 5), which are greater than one. It was proven that rainfall with a higher mean rainfall intensity led to λ_1 exceeding 13 m^3·ha^{-1} rather than λ_2 exceeding 0.32 and indicates the need for stormwater network modernization. The κ value is strongly influenced by the calibrated SWMM parameters describing retention catchment (Figure 5 a, b, c, d). It was found that increases in β and n_{sew} led to a decrease in the κ value (Figure 5a and 5b). This means that the relative difference between the rainfall duration indicating the need for modernization in the context of λ_1 = 13 m^3·ha^{-1} and λ_2 = 0.32 decreased. An increase in n_{imp} and D_{imp} led to an increase in κ, as indicated by an increase in the rainfall duration t_{r2} relative to t_{r1} conditioning λ_2 = 0.32 and λ_1 = 13 m^3·ha^{-1} (Figure 5c and 5d).

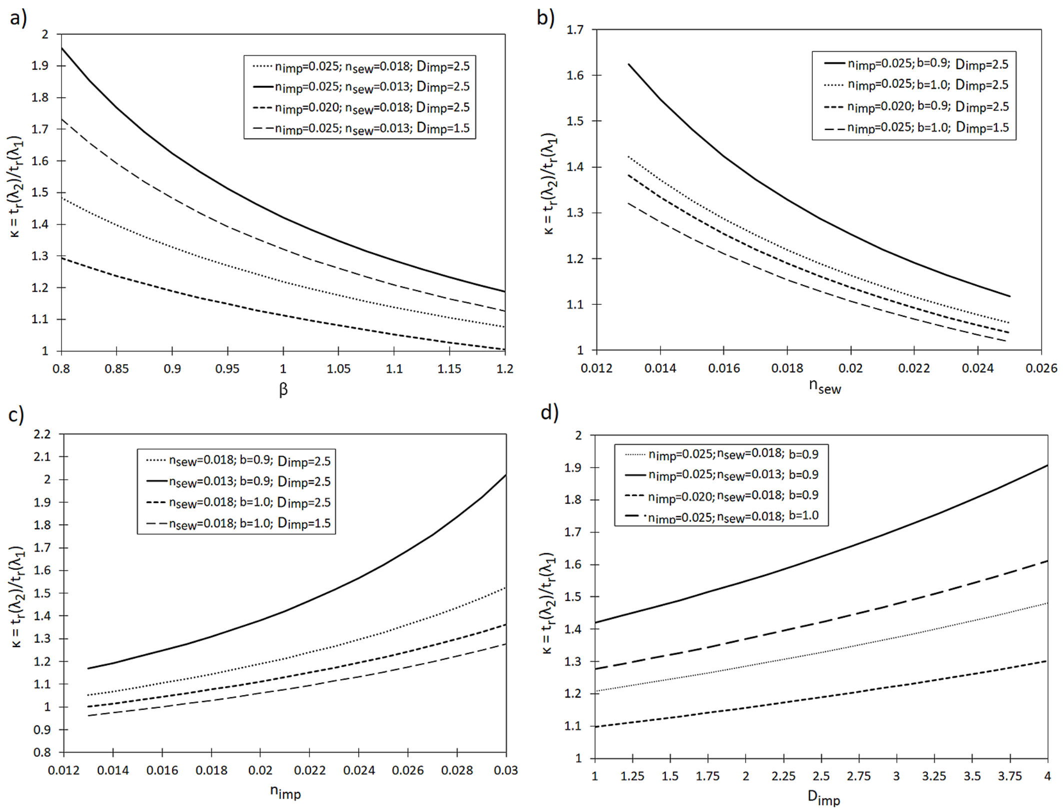

Figure 5. Influence of the identified SWMM parameters. (a) β, (b) n_{sew}, (c) n_{imp} and (d) D_{imp} on the value of κ for C = 5

Discussion

Extensive sensitivity analysis

Based on the proposed sensitivity coefficients for the logistic regression model, calculations of their values with respect to the identified SWMM parameters were performed. The conducted calculations showed that the correction coefficient for the percentage of impervious areas (β), Manning's roughness coefficient of sewer channels (n_{sew}) and Manning's roughness coefficient for impervious areas (n_{imp}) have key influences on the specific flood volume and degree of flooding. The calculation results obtained in this paper are consistent with those of Fu et al. [44], who performed simulations for an urban catchment (200 ha) in the UK and showed the significant influence of the runoff coefficient on the volume flooding from each manhole. This was consistent with the calculations of Brown et al. [45] that were conducted for a large catchment in southern England. Using the results of hydrograph measurements as the basis of the GLUE + GSA simulations, they showed that the retention depth of impervious areas and Manning's roughness coefficient of sewer channels have a strong influence on the results of catchment runoff calculations. The abovementioned calculation results were also consistent with those of Thorndahl [46], who, while performing a continuous simulation of the stormwater network operation in the Freylev catchment, developed a statistical model using the FORM method to calculate stormwater flooding from each manhole. The calculation results obtained in the present study, compared to the study of other authors [45, 47], showed a large influence of the rainfall duration and the return period on the sensitivity coefficients. The consideration of rainfall intensity, which is usually omitted at this stage of sensitivity analysis, is of great importance from the point of view of selecting rainfall-runoff events for the identification of SWMM parameters and validation of the hydrodynamic catchment model [48]. The results obtained indicate that omitting rainfall intensity at the sensitivity analysis stage can lead to problems in determining which SWMM parameters can be omitted at the calibration step. This problem was signaled by Fraga et al. [30], who performed sensitivity calculations for each rainfall event using the GSA method, obtaining different values of sensitivity coefficients.

The criteria for the functioning of the rainwater drainage network analysis

The consideration of two criteria of stormwater network operation (i.e., specific flood volume and degree of flooding) enabled the evaluation of the operation of the drainage system in the context of making decisions concerning its modernization, i.e., taking corrective measures including sewer channels cleaning or reducing their roughness coefficient. The applied solution allowed the assessment of the performance of the stormwater system at the spatial scale in the qualitative aspect (degree of flooding) and in the quantitative aspect (specific flood volume). Current methods tend to focus on a local approach in which a hydrodynamic model of the catchment is developed using landscape and manhole design data, which are important for determining the depth and area of flooding [16, 49]. These models are complex to implement and require data that are not always easy to obtain, which can lead to problems with their calibration. The solution applied in the present study, compared to the currently used methods [17] in which a criterion for the operation of the sewage network is imposed, allows its optimal selection on the basis of κ values considering the variability of calibrated SWMM parameters.

CONCLUSIONS

Currently, the analysis of stormwater network operation under hydraulic overload conditions is a frequently addressed issue because the simulation tools are the basis for decision making on the modernization of the drainage system. For these tools to be useful for making such decisions, it is necessary to calibrate the models. In the present study a multicriteria methodology for simulation of specific flood volume and the degree of flooding was provided, using the logistic regression method. The developed simulators enable the need for repair actions to be indicated and allow the determination of the key parameters of the SWMM model that need to be identified, which is important from the point of view of planning field tests prior to its calibration. The approach adopted in the study allows reducing the uncertainty of the simulation results and improving the reliability of the obtained predictions, which is reflected in the achievement of the assumed effect of decrease in hydraulic load.

Based on the sensitivity coefficients determined, the influence of calibrated SWMM parameters on the calculations results of the specific flood volume and degree of flooding was identified. The results of the calculations showed that the correction coefficients for the percentage of impervious areas, impervious area retention and Manning's roughness coefficient of sewer channels had a key influence on the specific flood volume, and the degree of flooding. Moreover, given that the values of sensitivity coefficients depended on rainfall intensity, conducting the assessment to appropriately select rainfall-runoff events for identifying and validating SWMM parameters seems to be advisable.

Considering the usefulness of the obtained calculation results, further analysis is advisable to establish the minimum period of continuous rainfall measurements for the development of logit models, then verify the obtained models for the calculation of specific flood volume and the degree of flooding for urban catchments with other characteristics and determine the range of their applicability. It is also advisable to consider extending the models with the characteristics of other urban catchments (area, catchment imperviousness, slope, land use, etc.) and stormwater networks (channel retention, diameters including slope, length of pipes, etc.) and finally their spatial arrangement.

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