Review 1

This manuscript presents a model to simulate specific flood volume considering both catchment and stormwater network characteristics, and including a module to calculate and indicate possible failure of the stormwater network, which is an interesting topic. The presented model algorithms consist of nine modules (Section 3 methodology): eight modules are a replication of what were developed and published by the same lead author; i.e., Szeląg et al. 2021 (e.g., hydrodynamic model- module 2 in the manuscript, sensitivity test considering uncertainty- modules 3, 4, 6, 7) and Szeląg et al. 2022 (Logistic regression and its application to stormwater network - modules 5, 8) over the same catchment. Module 1 in this manuscript addresses 9 sub-catchments (Table 1, though mentioned as 8 in line 128) to be simulated, which the items of characteristics are applied the same way as above-mentioned articles but the resulted values shown in Table 1 are slightly different depending on the differently selected sub-catchment.

Szeląg, B., Kiczko, A., Łagód, G., De Paola, F.: Relationship between rainfall duration and sewer system performance measures within the context of uncertainty, Water Res Manage., 35, 5073 – 5087, https://doi.org/10.1007/s11269-021-02998- x, 2021

Szeląg, B., Suligowski, R., De Paola, F., Siwicki, P., Majerek, D., Łagód, G.: Influence of urban catchment characteristics and 760 rainfall origins on the phenomenon of stormwater flooding: Case study, Environ. Model. Softw., 150, 105335, https://doi.org/10.1016/ j.envsoft.2022.105335, 2022

It is OK to replicate a method, particularly if it is a part of a system (of several modules) that requires to be run to test newly proposed hypotheses and questions or in quite different catchments for the model adaptation, given both clear objectives and well explained results. However, this manuscript lacks clear presentations of objectives, newly focused methods and results, and solid evidence of impact: e.g., • Some presentations of modules 1 to 8 and corresponding results were adopted too much from the two articles above with slight changes in sample events, subcatchments, and letters in the equation without providing clear explanation written in this manuscript; e.g., specific flood volume is defined in this manuscript as in eq.1 without referring as "specific flood volume", then later appears in line 97 and in line 87 as λ, (which was used and better explained in Szeląg et al. 2021). This example can be a trivial, but such way of presenting the adopted methods and results on modules 1 to 8 (Section 2 – missing explanations on DC, S1, boundary of sub-catchments, and why divided in this way; more can be found in Sections 3.1 to 3.7 as well as Sections 4.1-4.5) made the manuscript unclear and confusing if the results were obtained from this work or speculated from the previous work. This made the Section of conclusion weak as well; e.g., the authors conclude "no other previous study has included such a broad scope of analysis" (line 550), however they adopted their previous work and presented similar results here providing similar messages and interpretation.

Response 1

Dear Reviewer, Thank you for your comment. Indeed, aspects of uncertainty analysis (its effect on simulation results of specific flood volume and manhole overflow) and the use of a logistic regression model were addressed in the publications mentioned above. However, the data and context of their use was different than in the manuscript submitted for review.

In connection with this, let us clarify it. Namely, in the manuscript: "Influence of urban catchment characteristics and rainfall origins on the phenomenon of stormwater flooding: A case study" developed a logit model based on rainfall data and catchment characteristics on identifying only the phenomenon of stormwater flooding in the catchment. These analyses were performed for sub-catchments A, B, C, D (Fig. 1), which was justified by their location and the possibility of conducting a field survey simultaneously in two catchments during a single rainfall event.

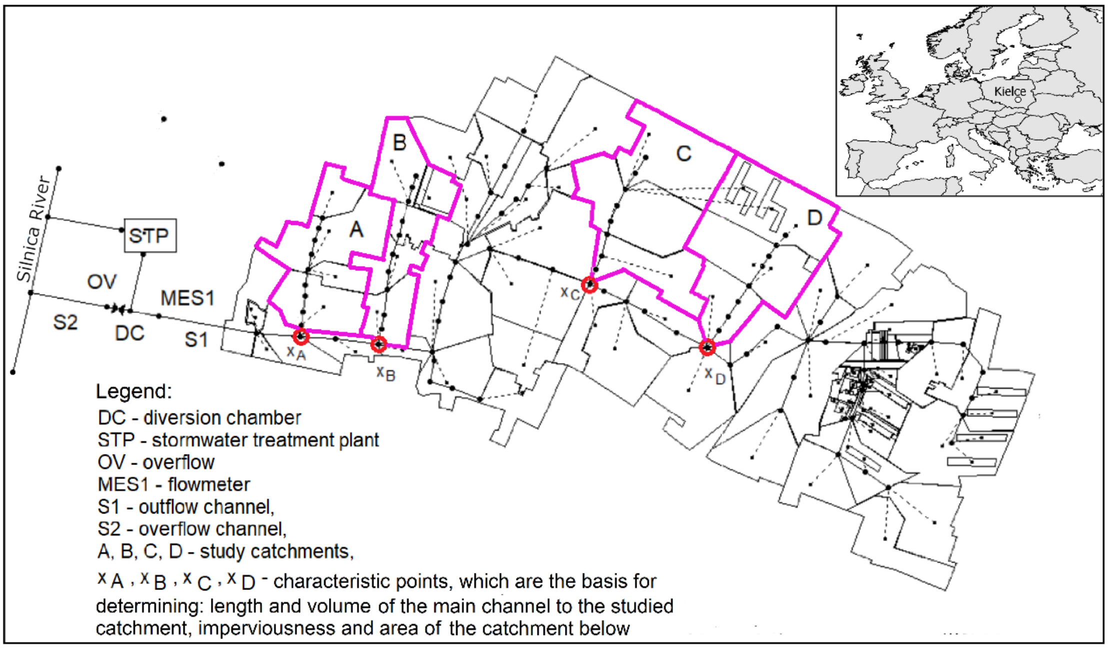

Fig. 1. Study catchments for the determination of a logit model for stormwater flooding identification (Szeląg et al. 2022)

The 159 rainfall events observed during the period 2008 - 2019 were used for this purpose. Although the feasibility of using the developed model to identify stormwater flooding in a catchment during a single rainfall - runoff event was demonstrated, because the field study covered only 4 catchments, the resulting relationships in the manuscript by Szeląg et al. (2022) did not fully reflect the phenomenon of stormwater flooding occurrence and did not take into account the volume of stormwater flooding

The limitations of the developed model are highlighted in this work. In the context of literature data (Jato - Espino et al. 2018, Li and Willems 2020), improved predictive capability was possible by using a hydrodynamic model which enables to perform simulations. Nevertheless, the authors focused on developing simulators to identify flooding from a single manhole based on simulation results with a calibrated hydrodynamic model. However, in the context of uncertainty analysis, it is known that there is an interaction between the calibrated parameters, resulting in many possible combinations of SWMM parameters for which identical matches between computational results and measurements are obtained. In this context, it is difficult to unambiguously consider as correct the results of a simulation of a well stormwater flooding, for example, ignoring the uncertainty of the calibrated parameters.

Once we identified this problem, we concluded that it was necessary to determine the effect of uncertainty in the calibrated SWMM model parameters on the results of the parameter calculations that form the basis for evaluating the performance of the drainage network. A literature study (Siekman and Pinekamp 2011) indicated that the appropriate parameters for evaluating the performance of a drainage system are specific flood volume and manhole overflow (degree of flooding). These calculations were made for the entire urban catchment, without sub-catchment division in the paper: "Relationship between rainfall duration and sewer system performance measures within the context of uncertainty". However, is the value of specific flood volume determined for the whole catchment an adequate measure of stormwater system performance evaluation and should it serve as a basis for decision making?

Of course not, because it is important to answer the question which part of the drainage system needs to be upgraded. To meet this objective, there would be a need to separate sub-catchments in the model where specific flood volume would be determined. In the manuscript: , "Relationship between rainfall duration and sewer system performance measures within the context of uncertainty" such analyses were not performed. Indeed, in the manuscript by Szeląg et al. (2021) the influence of SWMM model parameters on specific flood volume was analyzed, but the data were presented for a single rainfall only, and thus the obtained relationships were of a preliminary nature and only illustrated certain trends, but not strict relationships that can be practically used. To determine the relationship between specific flood volume and SWMM model parameters in the work of Szeląg et al. (2021), the results of sewer operation simulations were used in which 5000 simulations were performed (considering the combination of SWMM parameters) for each independent rainfall event.

The obtained preliminary results turned out to be interesting and bearing in mind that so far no simulator of specific flood volume has been developed that would simultaneously take into account the characteristics of the catchment, the stormwater network and the parameters of the SWMM model, an attempt was made to build one. For this purpose, sub-basins were separated in the model using the developed hydrodynamic model, which is a common practice. In this approach, the authors were guided by the limitations of the obtained logit model obtained in the paper: , "Influence of urban catchment characteristics and rainfall origins on the phenomenon of stormwater flooding: A case study". The aim was not to simulate similar processes, because the probability of a specific flood volume and the probability of a stormwater flooding are quite different independent parameters. The use of measured data of stormwater flooding in the catchment (Szeląg 2022), as well as the adopted calculation methodology clearly confirmed the lack in the developed model.

Taking into account the limitations of the models developed so far and the simulation results in the works of Szeląg et al. (2021, 2022), Jato - Espino et al. (2018), Li and Willems (2019), a simulation experiment was planned involving the separation in the analyzed catchment, sub-catchments for which simulations of specific flood volume were performed for the separated rainfall events in the observational series of measurements (2008 - 2018). Thus, the methodology proposed in this paper is a compilation of experiments, but not of computational results obtained in the works: ,,Influence of urban catchment characteristics and rainfall origins on the phenomenon of stormwater flooding: Case study", "Relationship between rainfall duration and sewer system performance measures within the context of uncertainty". Efforts were made to develop a model that would reflect the operating conditions of the stormwater system (in the context of hydrology), but also to increase the amount of data to build the model, which is an indirect method to increase its accuracy (if the results of calculations with the logit model proved to be unsatisfactory, more advanced methods of machine learning would be applied). Using such a modified methodological approach to preparing data for model building, a logit model was developed that has nothing in common with the model obtained in the work of Szeląg et al. (2022).

Dear Reviewer, The objective of the present analyses was primarily to develop a tool to determine the influence and interaction between the calibrated parameters of the SWMM model and the specific flood volume taking into account both catchment characteristics, stormwater network and rainfall data. Based on the developed model, it was determined that at the stage of sensitivity analysis, boundary conditions are important. The values of catchment characteristics determine the influence of SWMM model parameters on stormwater flooding, which is very important from the point of view of model calibration, selection of techniques for identifying catchment and stormwater network characteristics before attempts are made to create a hydrodynamic model. The methodology obtained in this study actually answers a number of questions that can be initially answered before the construction of the hydrodynamic model is started. This is extremely important as it allows for optimization of the model calibration methodology. The obtained results and the model can be used as a tool for preliminary identification of requirements that must be fulfilled for the model to provide high agreement between the calculation results and measurements.

The manuscripts of Szeląg et al. (2021, 2022) only attempted a step-by-step methodology to identify the problem due to the enormous computational effort involved. As mentioned above 108 precipitation events were used to build the logit model (Szeląg et al. 2021), 90,000 simulations (16 rainfall events and 5000 simulations) were performed to determine the effect of uncertainty in the calibrated SWMM parameters, in the present problem the number of simulations is many times larger.

Undertaking such a complex problem indeed required preliminary analyses, which were necessary because in undertaking subsequent simulation problems we were unable to answer the question of whether it is possible to develop such a simulator.

In this manuscript, we tried to highlight the influence of catchment characteristics on the results of sensitivity coefficient calculations, which is important from the point of view of selecting SWMM model parameters for calibration, but also may be relevant at the stage of planning the location of measuring devices. In addition, efforts were made to focus on reflecting stormwater flooding conditions in catchments given the varying catchment characteristics. From this point of view, it would indeed be reasonable to attempt to compare the results obtained with the studies of other authors and to perform a preliminary verification of the model developed. It seems advisable to compare the results of the sensitivity analysis obtained by other authors. First of all, it is advisable to highlight the influence and interaction between catchment characteristics and SWMM parameters in the context of literature data and to demonstrate the usefulness of the developed model.

We would also like to mention that the results of calculations, which were obtained in the previous works: ,,Influence of urban catchment characteristics and rainfall origins on the phenomenon of stormwater flooding: Case study", "Relationship between rainfall duration and sewer system performance measures within the context of uncertainty" were not used for model building in this manuscript. Data for building the logit model (in this manuscript) were obtained by performing independent computer simulations over a period of 4 months.

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Siekmann, M., Pinnekamp, J., 2011. Indicator based strategy to adapt urban drainage systems in regard to the consequences caused by climate change. 12th International Conference on Urban Drainage, Porto Alegre (Brazil)

Li, X., Willems, P., 2020. A Hybrid Model for Fast and Probabilistic Urban Pluvial Flood Prediction. Water Resour. Res. 56. https://doi.org/10.1029/2019WR025128

Jato-Espino, D., Sillanpää, N., Andrés-Doménech, I., Rodriguez-Hernandez, J., 2018. Flood Risk Assessment in Urban Catchments Using Multiple Regression Analysis. J. Water Resour. Plan. Manag. 144, 04017085. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000874

In the text above, the considerations that were taken into account during the model building phase in the context of published articles (Szeląg et al. 2021, 2022) are thoroughly explained. These aspects are synthesized in the introduction to clearly state the purpose of the paper. The introduction with proposed modifications is provided below **(red color indicates proposed modifications).**

,,Climate change and urbanisation are major drivers of increased frequency and severity of hydraulic overloads in urban catchments, leading to flooding events, which cause decrease of life standard, material losses, traffic difficulties etc. (Petit-Boix et al., 2017; Chang et al., 2021). Therefore, criteria for assessing stormwater network operating were introduced, which should be taken into consideration both at the design stage and while planning corrective actions. According to these criteria, one of the key assessment parameters is a maximum number of stormwater flooding in return period (DWA – A118E, 2006; EN – 752, 2006). However, since this parameter has a typically qualitative character, some further modifications were proposed. Based on computation results for stormwater networks, Siekmann and Pinekamp (2011) defined the boundary values of specific flood volume which expressed the volume of stormwater per unit impervious area. Exceeding these values should be considered as a clear signal for decision-makers to implement the process of improving stormwater management in the catchment.

Mathematical modelling of the stormwater network provides significant support in a decision-making process. According to (Kirshen et al., 2015; Chen et al., 2016; Mignot et al., 2019), hydrodynamic catchment models are usually applied. For many years, the United States Environment

Protection Agency (EPA) has been developing computation tools to simulate stormwater network operation. One of the most common tools is the SWMM (Storm Water Management Model) program, (Baek et al., 2020; Behrouz et al., 2020). SWMM can be applied for a simplified simulation of stormwater runoff from a catchment, hydrographs in stormwater network as well as simulation of hydraulic overloads resulting in flooding (Teng et al., 2017; Cheng et al., 2019). Simulation results (hydrographs, specific flood volumes) can be burdened with uncertainty due to lack of data on catchment spatial development, stormwater network characteristics as well as due to limited number of rainfall – runoff episodes (high resolution measurements of rainfalls and flow rates), and interaction between identified parameters.

In order to reduce uncertainty, optimization of calibrated model parameters is applied (De Paola et al., 2016; Swathi et al., 2018; Awol et al., 2018). Currently, integrating sensitivity and uncertainty analysis, which is characteristic for mechanistic models, gains the highest popularity. In case of machine learning methods (Ke et al., 2020) identification of model structure requires implementation of advanced optimization algorithms (Mignot et al., 2019), while for sensitivity analysis Cateri Paribus, Shapley index (Yang et al., 2020) methods are used. According to literature reports (Cristiano et al., 2019) in most studies rainfall intensity impact is neglected at sensitivity analysis stage. This assumption leads to generalization. Moreover, it is contrary to the findings of Fraga et al. (2016) and Cristiano et al. (2016) who proved the significance of rainfall distribution to the following relationships: catchment characteristics – peak flow, specific flood volume – calibrated parameters of SWMM model etc. Simulations of outflow hydrographs, stormwater flooding with mechanistic models for urban catchments with diverse characteristics (different surface, imperviousness, density of stormwater network etc) showed huge discrepancies. Identification of relationship between SWMM and stormwater flooding is of high importance in the context of interactions between their numerical values, which was proved in a number of previous studies (Huang et al., 2018; Xingh et al., 2021). According to literature (Dotto et al. 2014; Teweldebrhan et al., 2020; Chen et al. 2018) , the most commonly used method of uncertainty analysis in urban catchments is GLUE (Generalized Likelihood Uncertainty Estimation) method. Szeląg et al. (2021) confirmed the impact of SWMM parameters uncertainty on computation of specific flood volume and of manholes overflow (without division into sub-catchments).

Due to the aforementioned circumstances, machine learning methods were applied to simulation of stormwater overflow. Thorndahl et al. (2008) based on simulation results of stormwater overflow from manholes, including uncertainty of calibrated parameters elaborated a model using FORM method. Jato-Espino et al. (2018) and Li and Willems (2020), conducting simulations with mechanistic models, appointed models for identification of overflow from a single manhole based on rainfall frequency, catchment characteristics and stormwater network characteristics. Application of those models for stormwater network management was limited and required huge burden of work as well as highly relevant data. Therefore, Szeląg et al. (2022) elaborated a model for identification of stormwater flooding in a catchment, however due a number of data used during model construction, the obtained relationship had a limited application. In the aforementioned models, interactions between catchment and stormwater network characteristics and catchment retention and stormwater system conductivity were neglected. In the context of catchment management, these factors are relevant for selection of the optimal solution (green infrastructure, channel retention) of amelioration of stormwater system operation. Neglecting of a single of these factors results in a reduced applicability of the obtained tool at the stage of spatial planning. Mechanistic models include the listed above conditions, however they require detailed data and can be used only for a specific catchment. Simulator is lacking, which would at the same time include catchment characteristics, stormwater network characteristics as well as identified parameters of mechanistic model, and can be applied for different urban catchments without the need of calibration.

~~Mathematical modelling of the stormwater network provides significant support in a decision-making process. According to (Kirshen et al., 2015; Chen et al., 2016; Mignot et al., 2019), hydrodynamic catchment models are usually applied. For many years, the United States Environment Protection Agency (EPA) has been developing computation tools to simulate stormwater network~~

~~operation, which allow for implementation of Green Infrastructure units in the catchment. One of the most common tools is the SWMM (Storm Water Management Model) program, which has been used in multiple studies (Baek et al., 2020; Behrouz et al., 2020). SWMM can be applied for a simplified simulation of stormwater runoff from a catchment, flow rates in stormwater network as well as simulation of hydraulic overloads resulting in flooding (Teng et al., 2017; Cheng et al., 2019). However, in order to establish the range of flooding, stormwater flow directions and water depth, the SWMM source code needs either modification or integration with other calculation tools (Sañudo et al., 2020; Shojaeizadeh et al., 2021). Moreover, the hydrodynamic model of a catchment requires calibration before it can be applied for stormwater management in a certain catchment area. Data on the spatial development of a catchment, stormwater network and high-resolution rainfall statistics and flow rate measurements are necessary to accomplish the calibration process. Yet, due to the multiplicity of the parameters, the problems encountered at the identification stage are quite frequent, which leads to uncertainty of results (Her et al., 2015; Knighton et al., 2016, Kiczko et al., 2018; Fong and Chui, 2020).~~

~~Optimization methods are frequently used to estimate parameters in hydrodynamic models (De Paola et al., 2016; Swathi et al., 2018; Awol et al., 2018). Model calibration can be divided into two stages: (1) sensitivity analysis, aimed at eliminating parameters that have an insignificant impact on results, and (2) uncertainty, which analyses interactions between parameters and identifies them based on empirical distribution. According to literature data (Zhang et al., 2019; Cristiano et al., 2019) local and global methods are applied for sensitivity analysis. However, the impact of rainfall intensity is neglected at the calculation stage, which affects model sensitivity results (Razavi and Gupta, 2015; Fatone et al., 2021) and can hinder an adequate selection of parameters at the calibration stage. Sensitivity analysis is limited to sub-catchments, and so it is impossible to predict the impact of catchment characteristics on calculation results. Moreover, the impact of calibrated parameters of hydrodynamic models in relation to catchment characteristics is unknown. This issue is of major significance for catchment modelling and selecting proper methods for identifying catchment characteristics including retention of impervious and permeable areas, roughness and slope of terrain, as well as for measuring Manning roughness coefficient for channels (Fraga et al., 2016; Kelleher et al., 2017). The accuracy of these measurements affects the uncertainty of the results obtained and means that some parameters may be discounted. The next stage of model calibration is uncertainty analysis (Chen et al., 2018; Teweldebrhan et al., 2020; Kim et al., 2021). According to Dotto et al. (2014) and Chen et al. (2018) the GLUE method (Generalized Likelihood Uncertainty Estimation) is currently the most frequently used. Computations confirmed that the uncertainty of calibrated parameters of hydrodynamic models has considerable impact on simulation results (Meresa and Romanowicz. 2017; Kiczko et al., 2018; Szeląg et al., 2022).~~

~~Considering the problems associated with calibrating hydrodynamic models, machine learning methods can offer a solution for modelling and assessing how stormwater networks operate. The structure of these models, based on the gathered measurement data, is identified at the so-called learning stage, and the empirical coefficients are also determined. Then, the appointed model is tested using independent data. The calibration of such a model is simpler in comparison to hydrodynamic models due to the fact that a number of advanced statistical methods are already implemented in computing packages. So, a basic knowledge on their operating is enough to establish a simulation model (Hutchins et al., 2016). A number of machine learning algorithms (boosted tree, random forest, neural network, machine automata) have already been applied in modelling hydraulic overload and flooding in urban catchments, as discussed in detail by (Yu et al., 2015; Ke et al., 2020; Yang et al., 2020). However, until now there have been no attempts to construct models (simulators) that might identify specific flood volume as a tool for evaluating the efficacy of existing stormwater systems and identifying a need for corrective actions. This issue is of tremendous significance because most applied models are defined for single catchments, which means that they are not universal in character and do not offer the possibility of correcting the catchment retention, catchment characteristics or stormwater network. This considerably limits the application of such tools in stormwater management in the catchment.~~

In our study, a novel algorithm for creating a simulator to predict specific flood volume is developed. In the proposed approach, the stormwater flooding is related to rainfall data, catchment characteristics and calibrated SWMM model parameters, which enables this tool to be implemented for different catchments with various characteristics, both at the stage of spatial planning, corrective actions of stormwater network (optimization of canal retention and terrain retention) and during the daily operation of stormwater networks. Therefore, the proposed model is an alternative to SWMM model, does not require calibration and allows for assessment of stormwater system operation even in case of limited data set. In the adopted algorithm, an innovative sensitivity coefficient was defined, allowing for analysis of dependencies between SWMM parameters (width of runoff path, retention of impervious areas, Manning roughness coefficient of impervious areas, accuracy of identification of impervious areas, Manning roughness coefficient of canals) on specific flood volume for adopted rainfall data and catchment characteristics. Procedures in the algorithm allow for analysis of stormwater network operation and for planning of corrective actionss with regard to uncertainty of SWMM parameters. Subsequent computation stages of the algorithm based on the measurement data from an urban catchment in Kielce are presented in the article."

Review 2

Some presentations of modules 1 to 8 and corresponding results were adopted too much from the two articles above with slight changes in sample events

Response 2

Dear Reviewer, it is a fact the algorithms are similar, but they involve different data. The data for building the logistic regression model to identify the stormwater flooding (Szeląg et al. 2022) is different from that for simulating the specific flood volume. It is clear from the comments cited above that the calculation results reported in Szeląg et al. (2021, 2022) are different than those presented in this manuscript. Nevertheless, to make this clear and readable in the revised manuscript it is planned to highlight the previous calculation results and refer to the algorithms developed in the previous manuscripts. Proposals for the planned revisions are given below.

,,An innovative algorithm for creating a simulator to identify a specific flood volume was proposed (Fig. 2). In contrast to existing algorithms in use, in the adopted approach, a wider scope of computation was applied, linked with analysis of model sensitivity and the impact of uncertainty of calibrated SWMM model parameters on the probability of a stormwater network failure

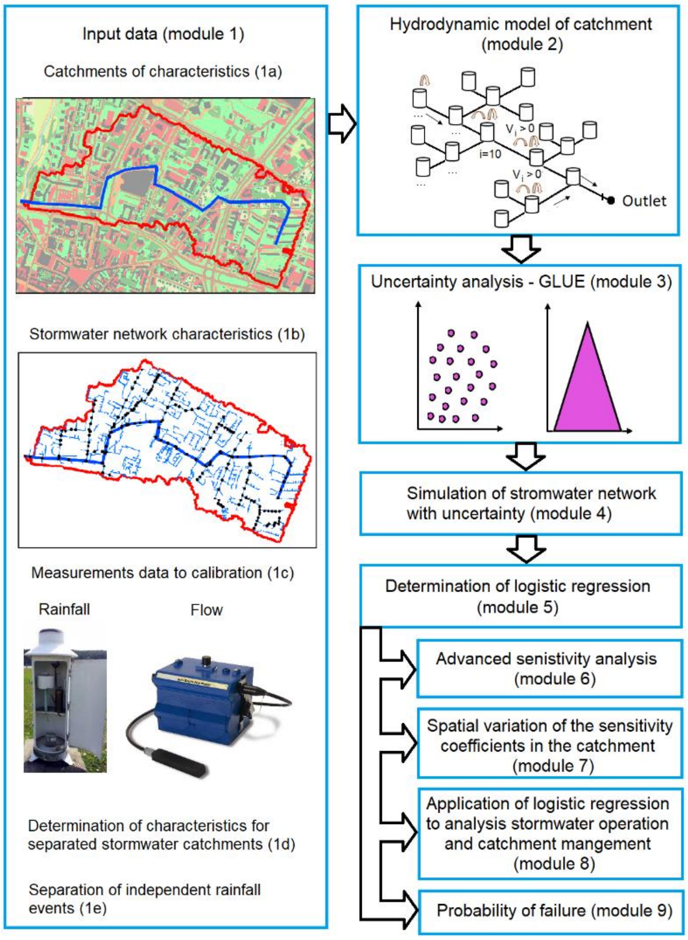


Figure. 2. Algorithm for developing an advanced model to simulate a specific flood volume (situation maps in module (1a), (1b) by Walek (2019).

A failure is defined as a state of operation of a stormwater drainage system (assumed rainfall load) in which hydraulic overloading occurs, channel capacity is exceeded, resulting in a specific flood volume of not less than 13 $m^3 \cdot ha^{-1}$. This requires corrective actions of the system and reduction of the runoff from the catchment by implementing rainfall management systems (alternatively improving the efficiency of the existing type of permeable surfaces, rainwater reservoirs, etc.), increasing sewer retention. Proposed methodology is based on extension of algorithms given by Szeląg et al. (2021, 2022). In contrast to previous studies (Szeląg et al. 2022), in the current approach the qualitative criterion of stormwater network operation (occurrence of flooding) was replaced by a quantitative criterion – specific flood volume. A simulator for identification of specific flood volume was developed based on rainfall data, catchment characteristics, stormwater network characteristics, SWMM parameters (the width of runoff path, retention volume of impervious areas, Manning roughness coefficient of impervious areas, precision of identification of impervious areas, Manning roughness coefficient of channels). Proposed model is an alternative for mechanistic model (Szeląg et al. 2021). At the same time, it also allows for evaluation of the need of corrective actions of stormwater network. Moreover, in contrast to existing algorithms in use, in the adopted approach, a wider scope of computation was applied, linked with analysis of model sensitivity and the impact of uncertainty of calibrated SWMM model parameters on the probability of a stormwater network failure. A failure was defined as exceedance of certain specific flood volume which points out that corrective actions of the stormwater network is necessary. The value of a specific flood volume was defined as volume of stormwater flooding per unit impervious area, which can be expressed by the following formula (Sinekamp and Pinekamp, 2011):

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

where: V_t – volume of stormwater flooding from i-th manhole of the stormwater network, K – number of manholes, A_{imp} – impervious area. Sinekamp and Pinekamp (2011) based on continuous simulations with hydrodynamic models for three urban catchments found that the specific flood volume ranged from 0 - (>20) $m^3 \cdot ha^{-1}$. On this basis, they established limiting κ values expressing the need to improve the operating conditions of the drainage system. They showed that for κ > 13 $m^3 \cdot ha^{-1}$ the drainage system requires adaptation This was also confirmed by the calculations of Kotowski et al. (2014) for the catchment in Wroclaw and Szeląg et al. (2021) for the catchment in Kielce. This allows us to conclude for urban catchments (Poland, Germany) that the κ value quoted above can be a criterion for making corrective actions of the drainage network.

The proposed computation algorithm consists of 9 modules. ~~The proposed computation algorithm consists of 11 modules. Module (1) provides data for development of hydrodynamic model of a catchment, such as catchment characteristics (1a) – spatial development, slope of the terrain etc., characteristics of stormwater network (1b) – diameters, lengths, channel slopes, manhole ordinates, etc., and measurement data regarding rainfalls and flow rates for calibration (1c). In this module the catchment is divided into sub-catchments along the main intercepting stormwater channel and the characteristics of sub-catchments are defined (1d). Inside module (1) the long-term rainfall series are also implemented and subsequently separated into independent rainfall events (1e). The data from module 1e are used for development of mathematical model of a catchment in SWMM program (module 2).~~ Developed algorithms (Szeląg et al. 2021, 2022) consist of input data in module 1 (catchment characteristics – 1a, stormwater network characteristics – 1b) used for development of hydrodynamic model (module 2). In module 3 the rainfall – runoff episodes are included which are the basis for uncertainty analysis by GLUE method. In module 1 the independent rainfall episodes are also included (1c) for simulation of stormwater network operation. In the module 4 simulations of stormwater network performance are computed for independent rainfall events determined in module (1c) and the values of specific flood volume for sub-catchments determined in module (1). Based on the simulation results and the assumption that when specific flood volume exceeds

13 $m^3 \cdot ha^{-1}$ the continuous values are transformed to binary data (which is discussed in detail in section 3.4) a logistic regression model is developed (module 5). This model is subsequently used to determine the sensitivity coefficients for calibrated SWMM parameters with regard to rainfall intensity and catchment characteristics (module 6).Using adopted rainfall data, the sensitivity coefficients of SWMM model parameters for sub-catchments are computed and maps showing sensitivity changes in catchment scale are drawn (module 7). While the model is applied to identify stormwater flooding, the possible methods for improving stormwater network operating are analysed inside module 8. Computations using the developed algorithm consist of the following steps:

1) collecting of the input data (catchment characteristics – 1a, stormwater network characteristics – 1b, rainfall – runoff episodes – 1c), separation of independent rainfall episodes – 1d, determination of characteristic of sub-catchments – 1e,

2) development of hydrodynamic model (module 2) based on catchment characteristics (1a) and stormwater network characteristics (1b),

3) conducting of uncertainty analysis with GLUE method (section 3.3) using hydrodynamic model of a catchment based on rainfall – runoff episodes (1d),

4) using independent rainfall episodes (1d) simulations with hydrodynamic model including uncertainty of calibrated parameters according to points (4a, 4b, 4c) are conducted;

a) simulation of SWMM parameters (tab. 1) using the results of uncertainty analysis (5000 samples),

b) simulation of stormwater network operation during independent rainfall episodes (1d) including uncertainty (4a),

c) computation of specific flood volume in each sample of independent rainfall episodes in sub-catchments; transformation of determined κ values to classification data (section 4a),

5) determination of logistic regression model based on results of computations in point 4c ,

6) sensitivity analysis:

a) computations of sensitivity coefficients (with regard to SWMM parameters) for assumed rainfall data and catchment characteristics,

b) computations of sensitivity coefficients for sub-catchments (J, K, L, M, N, O, P, R, S),

7) application of developed logistic regression model for amelioration of stormwater network operation,

a) analysis of the impact of corrective actions on sensitivity coefficients in sub-catchments,

8) analysis of failures occurrence.”

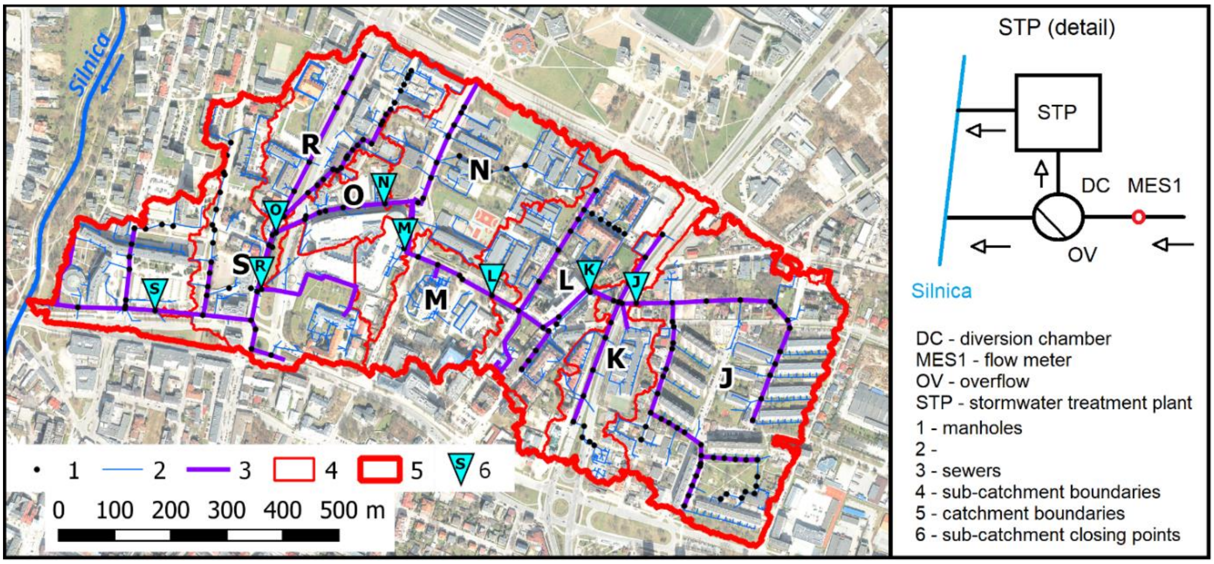
Review 3

Section 2 – missing explanations on DC, S1, boundary of sub-catchments, and why divided in this way

Response 3

The number and diversity of catchment characteristics used to build the model were insufficient from a simulation point of view. It is the number of data for model building that determines the results of calculations and the relationships obtained. In this context and bearing in mind that the aim of the analyses is an attempt to develop a universal algorithm for the use of hydrodynamic modeling, increasing the number of sub-basins for the planned experiment made it possible to increase the data for model building. We wanted to mention that the division of catchments and separation of sub-catchments was supported by the analyses of Walek (2018), who separated sub-catchments of side channels as part of his PhD dissertation and spatial data analyses for the whole of Kielce. The number of sub-catchments, their arrangement, was conditioned by the variation within them of the characteristics of the catchment, stormwater network, which is important from the point of view of the scope of applicability of the simulation model built.

Dear Reviewer, We kindly apologize, there was actually a description of the markings in the text missing from Figure 1, which has been corrected; Figure A.



Rys. A. Schematic of the catchment area with research sub-catchments.

Review 4

Module 9 (section 3 methodology, section 3.8 and section 4.7) looks newly incremented in this presented work. Although the authors mention briefly in the introduction of Methodology (line 145) its needs, this section is short and lacks clear explanation of the method and the results. In particular, section 4.7 needs better writing.

Response 4

Dear Reviewer, Thank you for your comment. The derived equations have been detailed. The derivation of equation (8) is given, the introductory part has been clarified and corrected in the context of literature data. The results of the calculations have been expanded. Compared to the previous version, in addition to the catchment characteristics, the characteristics of the sewer network and their influence on the probability of failure (pF) were analyzed. Proposed revisions to the manuscript are provided below.

3.8. Probability of stormwater network failure (module 9)

The probability of failure (Sun et al., 2012; Karamouz et al., 2013) was used to analyze the performance of the sewage network in a rainfall event. This is applicable assuming the probabilistic approach of the factors describing the phenomenon (volume of flooding, maximum flow, etc.). In this study, SWMM parameters were analyzed, as confirmed by Szeląg et al. (2021). In the calculations, a failure was defined as an episode (assumed rainfall data, catchment characteristics, sewer network, SWMM parameters described by *a posteriori distribution* - GLUE results discussed in Section 3.3) in which $\kappa \geq 13 m^3 \cdot ha^{-1}$ ($p_m \geq p_{m,cr}$) is exceeded. However, the probability of failure was calculated from the equation:

$$p_F = \frac{\sum_{j=1}^{N} Z_j}{N}, \ where: Z_j = \begin{cases} 1; \ p_m \geq p_{m,cr} \\ 0; \ p_m < p_{m,cr} \end{cases} \quad (7)$$

where: p_m – probability of specific flood volume (exceedance of this value indicates a failure), p_F – probability of the stormwater network failure in the event of rainfall, Z_j – function describing stormwater network operation, for $Z_j = 1$ – drainage system requires corrective actions; otherwise, i.e. $Z_j = 0$ – corrective actions is not necessary.

Based on equation (7) for the assumed characteristics (rainfall, catchment, drainage network), the operating conditions of the stormwater network were determined. A similar approach was used in the study of Fu et al. (2012) by limiting to probabilistic rainfall characteristics (Del Giudice, et al. 2013) and using a hydrodynamic model to simulate the drainage system. Fu et al. (2011) modified the above approach by focusing on the impact of uncertainty in the calibrated parameters on flooding; however, it was not possible to analyze retention, channel capacity on system performance. Hence, an algorithm is given to calculate the performance improvement of a sewer network in the context of failure probability (p_F) reduction. The above effect was obtained by introducing thresholds of maximum permissible values of Manning roughness coefficients of sewers $ns_{ew(m)}$. It was assumed that if the value of nsew (the value from the a posteriori distribution) exceeds the maximum permissible value - $n_{sew(m)}$ and determines the occurrence of failure ($Z_j = 1$) and the need to modernize the sewers, it should be corrected in such a way that $p_m < p_{m,cr}$. The above calculations were reduced to the following steps:

a) *a posteriori distribution* of calibrated SWMM model parameters (N = 5000 samples),

b) computation of probability of specific flood volume for N items and establishment of failure probability,

c) computation of the Manning roughness coefficient for channels when $p_m > p_{m,cr}$ from the following formula:

$$n_{sew} = \frac{1}{\alpha_{nsew}} \cdot \left[ln\left(\frac{p_{m,cr}}{1-p_{m,cr}}\right) - \left(\sum_{k=1}^{m-1} \alpha_k \cdot x_k\right) - \boldsymbol{X}_{rain} - \boldsymbol{X}_{Catchm} \right] \quad (8)$$

where: k = 1, 2, 3, …, m – calibrated SWMM model parameters; k = 1, 2, 3, …, m; α_{nsew} – estimated coefficient in logistic regression model for the Manning roughness coefficient for channels (the derivation of equation 8 can be found in the Supplementary Information),
d) establishment of empirical distribution describing the n_{sew} values calculated from Equation (8),
e) computation of n_{sew} values from Equation (8) for $n_{sew(un)} \leq n_{sew(m)}$ (where: $n_{sew(un)}$ – Manning roughness coefficients of channels computed in step (a), $n_{sew(m)}$ – maximal boundary (threshold) value of Manning roughness coefficient for channels), when $n_{sew(un)} \geq n_{sew(m)}$ to $n_{sew} = n_{sew(un)}$,
f) computation of probability of specific flood volume and probability of failure,
g) determination of empirical distribution (CDF) for n_{sew},
h) steps e – g are repeated r = 1, 2, 3, .., z – for different values of $n_{sew,max}$ and median values of $n_{sew(0.5)} = f(n_{sew(m)}, r)$ are denoted based on empirical distributions,
i) steps a–h are conducted for different catchment characteristics,
j) graph $p_F = f(n_{sew(0.5)})$ is drawn.

4.7. Probability of failure (module 9)

Based on SWMM model parameters determined via the MC method (Tab. S1), probability of failure (p_F) was computed for convection rainfall in Kielce with a duration time of t_r=30 min and P_{tot}= 9.61 mm. The following threshold values of $n_{sew(m)}$ were adopted for calculations: $n_{sew(m)}$ = 0.015 – 0.045 $m^{-1/3}\cdot s$, coupled with three variants of catchment characteristics: Imp = 0.36 and Impd =0.40; Imp = 0.35 and Impd = 0.40; Imp = 0.35 and Impd = 0.42. The impact of canal retention (Vk = 750, 850, 950 m^3); density of stormwater network (Gk = 0.0075, 0.0080, 0.0085 $m\cdot ha^{-1}$; Gkd = 0.005, 0.006, 0.007 $m\cdot ha^{-1}$) in upper and lower part of the catchment on probability of failure (p_F) was also analysed. The Manning roughness coefficients of the channels (n_{sew}) for the analysed variants were presented as empirical distribution (CDF). In Figure 8a, 9a the results for Imp = 0.36, Impd = 0.40 and Vk = 750, 850, 950 m^3 are presented, while other variants are shown in Figs. S25, S26.

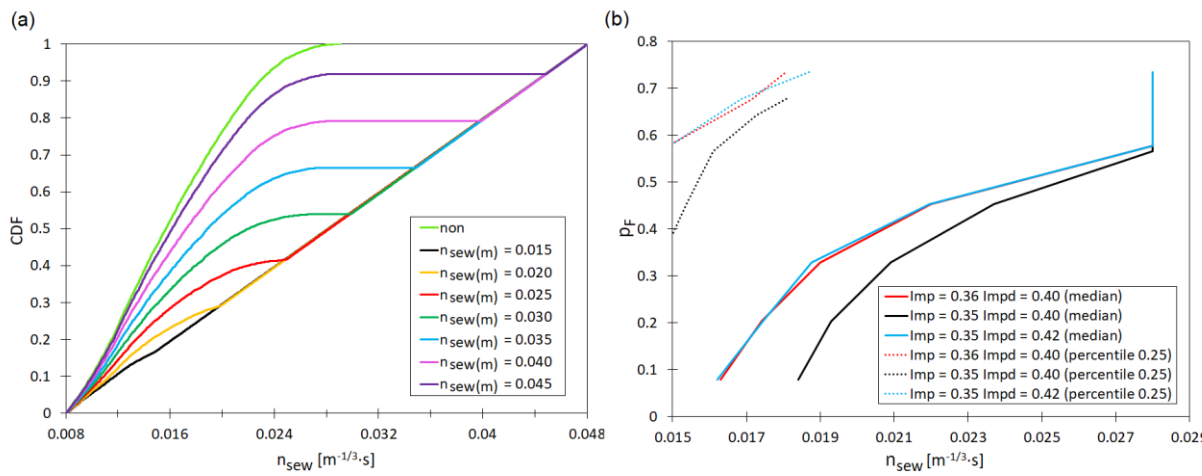


Figure 8. (a) Empirical distributions of threshold values of Manning roughness coefficients of channels (n_{sew}). (b) Impact of Manning roughness coefficient for channel on failure probability (p_F) in relation to Imp, Impd.

Figure 8b presents the impact of $n_{sew}=f(n_{sew(m)})$ for percentiles 0.25 and 0.50 (based on the curves in Fig. 8b, 9b, 9c, 9d, S25, S26 the values of the respective percentiles for the analysed $n_{sew(m)}$) on the probability of failure (p_F). Assuming that Manning roughness coefficients – $n_{sew(un)}$ determined by MC simulation which exceeds the threshold triggers the corrective actions of sewer pipes resulting in reduction of roughness below $n_{sew(m)}$ following the condition in which the stormwater network functions ($p_m = f(X_{rain}, X_{SWMM}, X_{Catchm}) > 0.75$ for an independent rainfall event), it was found out, that an appropriate decrease of percentiles (0.25 and 0.50 - median) leads to improved network operation and to a lower failure probability (Figs. 8a, 8b).

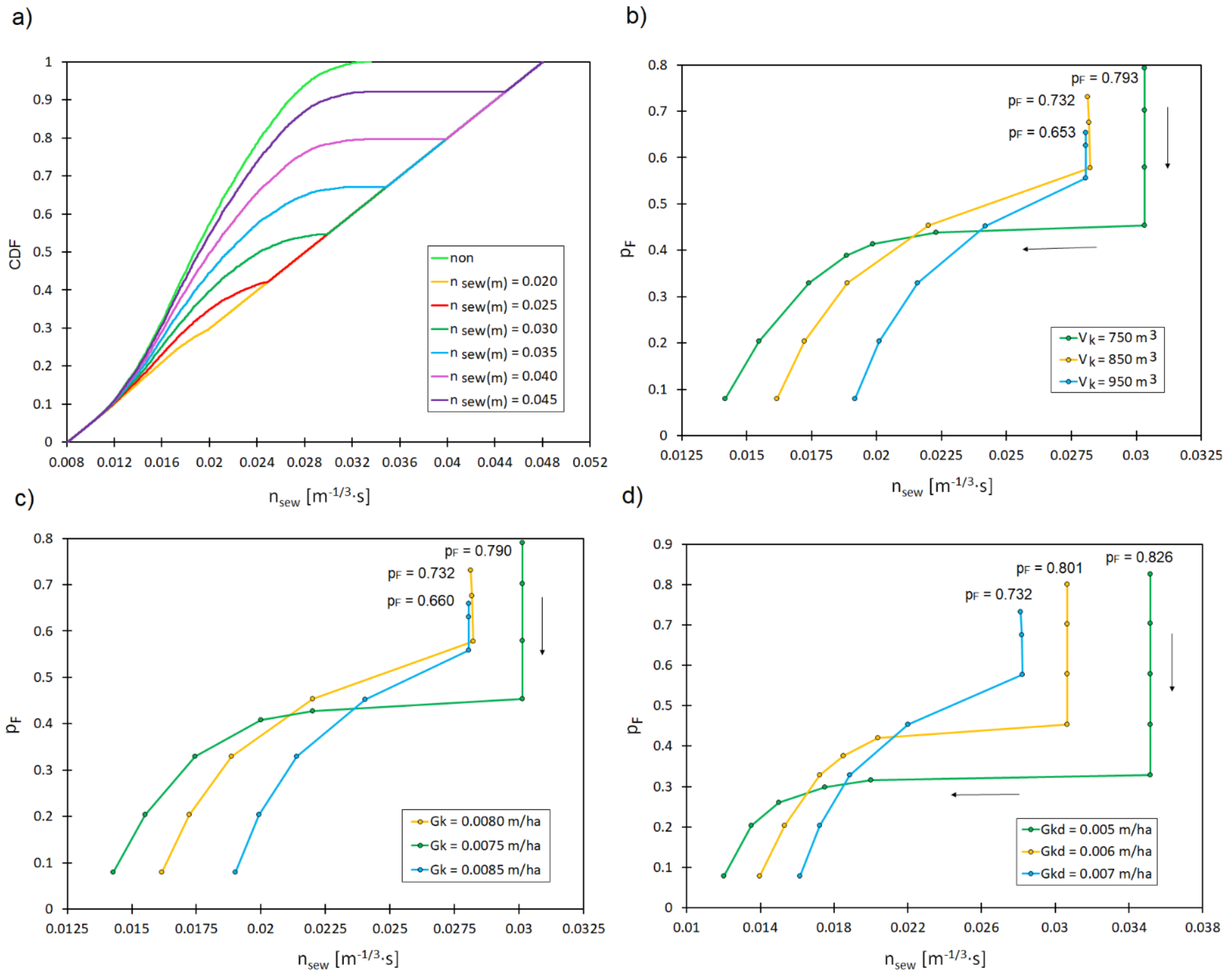


Figure 9. (a) Empirical distributions of threshold values of Manning roughness coefficients of channels (n_{sew}) for Vk = 950m^3. Impact of Manning roughness coefficient for channel on failure probability (p_F) in relation to: (b) Vk, (c) Gd, (d) Gkd.

Based on computation results, it was observed that the change of percentile 0.50 for n_{sew} for a sample from MC simulation leads to a decrease from 0.028 m$^{-1/3}$·s to 0.021 m$^{-1/3}$·s (as a result of correction $n_{sew(un)} < n_{sew(m)}$) and to improved stormwater network operation understood as a lower probability of failure (decrease of p_F from 0.68 to 0.42 for Imp = 0.36 and Impd = 0.40).These results confirm the significance of catchment characteristics (Imp, Impd) for the operability of a stormwater network. For Impd = 0.40, the reduction in catchment impervious area (Imp) from 0.36 to 0.35, at percentile n_{sew} = 0.019 m$^{-1/3}$·s results in a decrease in failure probability from p_F = 0.42 to p_F = 0.33.Great impact of canal retention (Vk) and density of stormwater network in the upper and lower part of a catchment (Gkd and Gk, respectively) on probability of failure p_F were indicated (Fig. 9). For n_{sew} < 0.0215 m$^{-1/3}$·s p_F reached higher values (max. 0.41) than for Vk = 850 m^3 and Vk = 950 m^3. The highest failure probability (p_F = 0.80) was obtained for Vk = 750 m^3 (n_{sew} = 0.031 m$^{-1/3}$·s), while the lowest p_F = 0.65 was obtained for Vk = 950 m^3 (Fig. 9b). Furthermore, the highest probability of failure p_F = 0.79 was obtained for Gk = 0.0075 m·ha^{-1} (n_{sew} = 0.031 m$^{-1/3}$·s), while the lowest for Gk = 0.0085 m·ha^{-1} (n_{sew} = 0.0276 m$^{-1/3}$·s) (Fig. 9c). It was established that for n_{sew} < 0.023 m$^{-1/3}$·s computed values of p_F for Gk = 0.0075 m·ha^{-1} and Gk = 0.0080 m·ha^{-1} are higher than 0.41. Moreover, the highest failure probability p_F for n_{sew} = 0.035 m$^{-1/3}$·s was equal to 0.82 for Gkd = 0.005 m·ha^{-1}, while for Gkd = 0.007 m·ha^{-1} it was 0.73.

Probability of stormwater network failure (derivation of the equation 11)

The probability of specific flood volume for the limiting value of $p_{m,cr}$ (exceeding it indicates that κ > 13 $m^3 \cdot ha^{-1}$ can be written as:

$$p_{m,cr} = \frac{exp(\boldsymbol{X})}{1+exp(\boldsymbol{X})} \tag{7}$$

By transforming equation (7), it can be stated that:

$$\boldsymbol{X} = ln\left(\frac{p_{m,cr}}{1-p_{m,cr}}\right) \tag{8}$$

Knowing that ***X*** is a linear combination of the independent variables, the relationship can be written:

$$\boldsymbol{X} = \boldsymbol{X}_{rain} + \boldsymbol{X}_{catchm} + \left(\sum_{k=1}^{m} \alpha_k \cdot x_k + \alpha_{nsew} \cdot n_{sew}\right) \tag{9}$$

Comparing sides (8), (9) obtained:

$$\boldsymbol{X}_{rain} + \boldsymbol{X}_{catchm} + \left(\sum_{k=1}^{m} \alpha_k \cdot x_k + \alpha_{nsew} \cdot n_{sew}\right) = ln\left(\frac{p_{m,cr}}{1-p_{m,cr}}\right) \tag{10}$$

By transforming equation (10), the value of nsew can be determined from the formula:

$$n_{sew} = \frac{1}{\alpha_{nsew}} \cdot \left[ln\left(\frac{p_{m,cr}}{1-p_{m,cr}}\right) - \boldsymbol{X}_{rain} - \boldsymbol{X}_{catchm} - \sum_{k=1}^{m} \alpha_k \cdot x_k\right] \tag{11}$$

Review 5

It was not clearly explained on certain threshold/coefficient values mentioned in the text (e.g., the threshold value of specific flood volume used 13 $m^3 \cdot ha^{-1}$ (line 69), is this derived also from one of the modules? If the method is applied to another catchment, how this threshold should be set?

Response 5

Sinekamp and Pinekamp (2011) based on continuous simulations with hydrodynamic models for 3 urban catchments found that the specific flood volume ranged from in the range of 0 - (>20) $m^3 \cdot ha^{-1}$. On this basis, they established limiting κ values expressing the need to improve the operating conditions of the drainage system. They showed that for κ > 13 $m^3 \cdot ha^{-1}$ the drainage system requires adaptation. This was also confirmed by the calculations of Kotowski et al. (2014) for the catchment in Wroclaw and Szeląg et al. (2021) for the catchment in Kielce. This allows us to conclude for urban catchments (Poland, Germany) that the κ value cited above can be a criterion for making decisions on sewer network corrective actions.

Thus, for the present conditions, the value of the specific flood volume can be taken as 13 $m^3 \cdot ha^{-1}$. A detailed methodology for the identification of limiting values for the simulation of sewer network operation in the context of drainage system corrective actions is given in Siekmann et al. (2009), Sinekamp (2010).

Review 6

The analyses regarding different sub-catchments (mostly Section 4.6, with the rainfall duration time of 30 min) need better explanation and writing. When selecting the different sub-catchments to decide the modernisation of stormwater network in practice, would the presented set-up of comparisons in different sizes but inclusive way (e.g., wouldn't J affect M as well?) be necessary and useful?

Response 6

Dear Reviewer, Thank you for your comment. In the present analyses, the successive sub-basins separated according to the main collector include the sub-basins separated above. For example, sub-basin K includes sub-basin J, and the differences in the probability values of specific flood volume indicate the influence of the sub-basins located in the sub-basin below on the conditions in the basin above. The same is true for the sensitivity coefficients; the analysis of their values in successive cross-sections made it possible to determine the variability of the influence of SWMM parameters on specific flood at the catchment scale. This is of great importance from the point of view of flow meter location. So far, the sensitivity of the model for simulation of stormwater flooding in sub-catchments separated according to the main collector has not been analyzed. Thus, the results obtained should be considered as novel. The relationship obtained in this way is important from the point of view of urban catchment hydrology. Unfortunately, the obtained variability of the sensitivity coefficients values does not take into account the local conditions within the side channels, but before the analyses it was not possible to determine the variability of the sensitivity coefficients. The results obtained indicate that there is a need for further analysis of the problem raised and to take into account in the modelling of the specific flood volume the location of the sub-catchment e.g. by side channels.

The obtained model can be used to analyse the performance of a sewerage network, however as successive catchments are created by connection the conditions occurring in them are averaged, which makes interpretation of the results difficult. Calculated probability value of specific flood volume for sub-catchment J (Fig. 1) may indicate $\kappa > 13\ m^3 \cdot ha^{-1}$ exceedance, the same may be true for sub-catchment K, despite the fact that in the catchment between cross-sections closing sub-catchments J, K there may be no κ exceedance. Indeed, this represents a limitation of the model, which, as stated above, indicates the need for its extension.

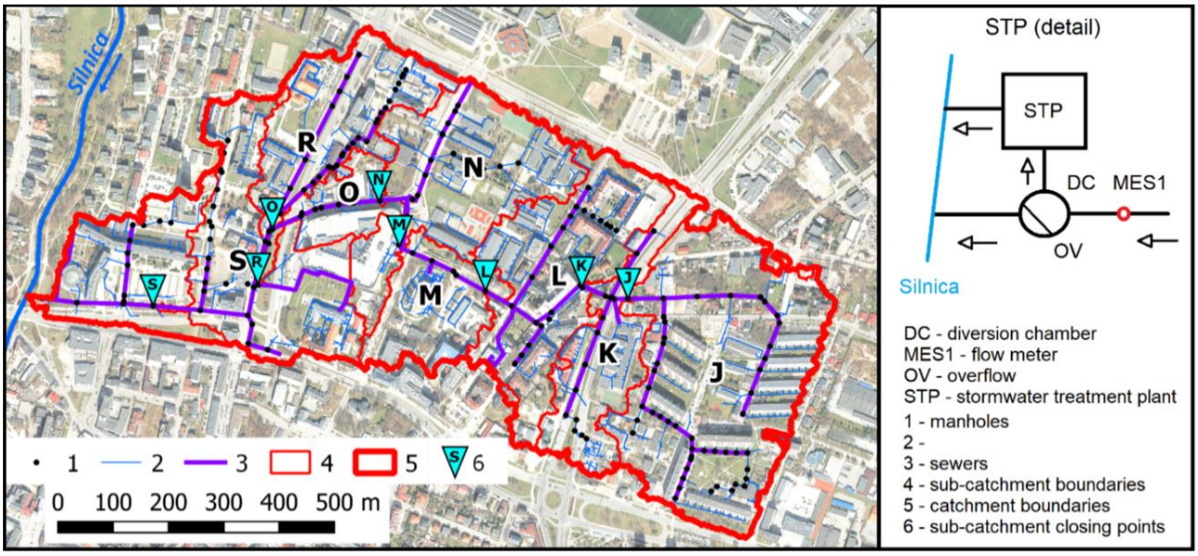


Fig. 1. Scheme of the catchment area covered by the analyses

Nevertheless, by analyzing the p_m values and the influence of individual catchment characteristics, sewerage network in successive sub-catchments, it can be determined whether hydraulic conditions are improving or deteriorating.

With these considerations in mind, the manuscript (Section 4.5, 4.6) highlights the influence of catchment, sewer network characteristics on the results of calculating the probability of specific flood volume and sensitivity coefficients. Sections 4.5, 4.6 are included below with the proposed modification.

4.5. Spatial distribution of sensitivity coefficients (module 7)

Based on the determined logit model described by Equation (9) and proposed relationship (6), the probabilities of specific flood volume for sub-catchments (p_m) were computed and sensitivity coefficients for calibrated SWMM parameters were determined (Tab. S1). A rainfall duration time of t_r = 30 min was adopted. According to Szeląg et al. (2022) this rainfall duration results in a specific flood volume in the analysed stormwater network. Computation results regarding p_m, S_β, S_{nsew}, S_{nimp} values (which had the highest impact on specific flood volume among SWMM parameters) are presented in Fig. 5. The probability of specific flood volume and other SWMM model parameters is presented in Figs. S16–S24. Based on the conducted calculations it was found out that for adopted rainfall data (convection rainfall with a t_r = 30 min) the problems with proper operating of stormwater network appear, which is confirmed by the values of specific flood volume for subsequent sub-catchments (Fig. 5a). Computations conducted with logit model (Szeląg et al. 2022) for adopted rainfall confirmed occurrence of stormwater flooding in the sub-catchments M, N, S.

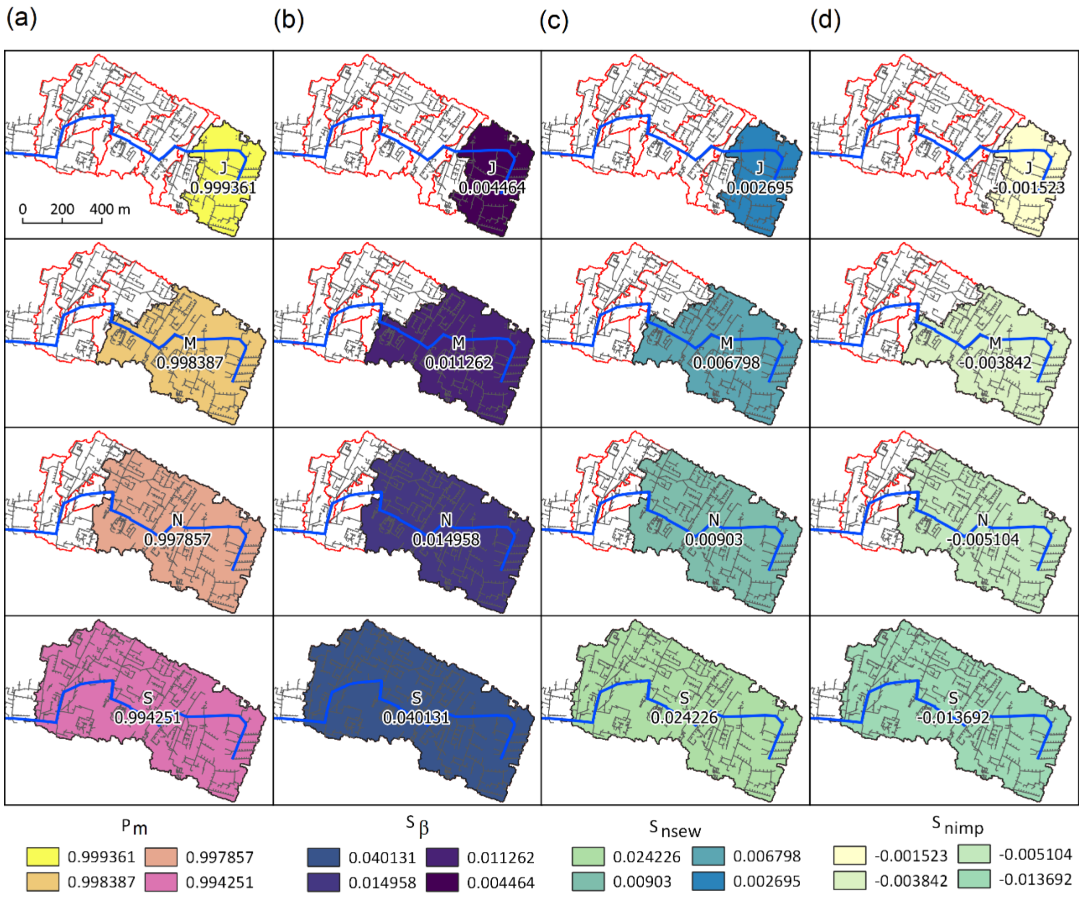


Figure 5. (a) Probability of specific flood volume (p_m); (b) sensitivity coefficient S_β; (c) sensitivity coefficient S_{nsew}; (d) sensitivity coefficient S_{nimp} in sub-catchments J, M, N, S.

The highest specific flood volume was obtained for sub-catchment J, while in the subsequent cross-sections (M,N,S) the values of p_m are lower (Fig. 4a). Variability of p_m values in sub-catchments J – S confirms that rainfall data have higher impact on probability of specific flood volume than parameters of SWMM model. The obtained results for sensitivity coefficients S_β, S_{nsew}, S_{nimp} confirm the results presented in section 4. Among the analysed SWMM parameters, the highest values of S_{xi} were determined for correction coefficient for percentage area (β). The calculations indicated that the lowest values of sensitivity coefficients (S_β, S_{nsew}, S_{nimp}) were obtained for catchment J and the highest for catchment S. It was proved that in sub-catchment S obtained sensitivity coefficients S_β, S_{nsew}, S_{nimp} are 2.68 times higher than in sub-catchment N and 9 times higher than in sub-catchment J. When ignoring catchment characteristics and stormwater network characteristics it can be proved that S_{nsew} (sub-catchment S) > S_β (sub-catchment S), and S_{nimp} (sub-catchment S) > S_{nsew} (sub-catchment N) > S_β (sub-catchment M) – Figs. 5b – 5d.

4.6. Implementation of logit model to analyse the operating of the stormwater network and catchment management (module 8)

Due to the fact that in the analysed stormwater network an exceedance of specific flood volume was observed, possible improvements to the network were considered in terms of correcting catchment imperviousness (Imp) as well as enhanced terrain retention and channel capacity. In variant I imperviousness Imp was reduced by 10%. In variant II d_{imp}=3.5 mm and n_{imp} =0.035 $m^{-1/3}\cdot s$ were corrected. Variant III was a combination of variants I and II, where channel conductivity was also increased (n_{sew}=0.012 $m^{-1/3}\cdot s$). The results of p_m computations are presented in Fig. 6, while Fig. 7 shows S_β for variants I, II and III for sub-catchments. Simulation results for the sensitivity coefficients of other SWMM model parameters (Tab. S1) and the probability of specific flood volumes are presented in Figs. S16–S24

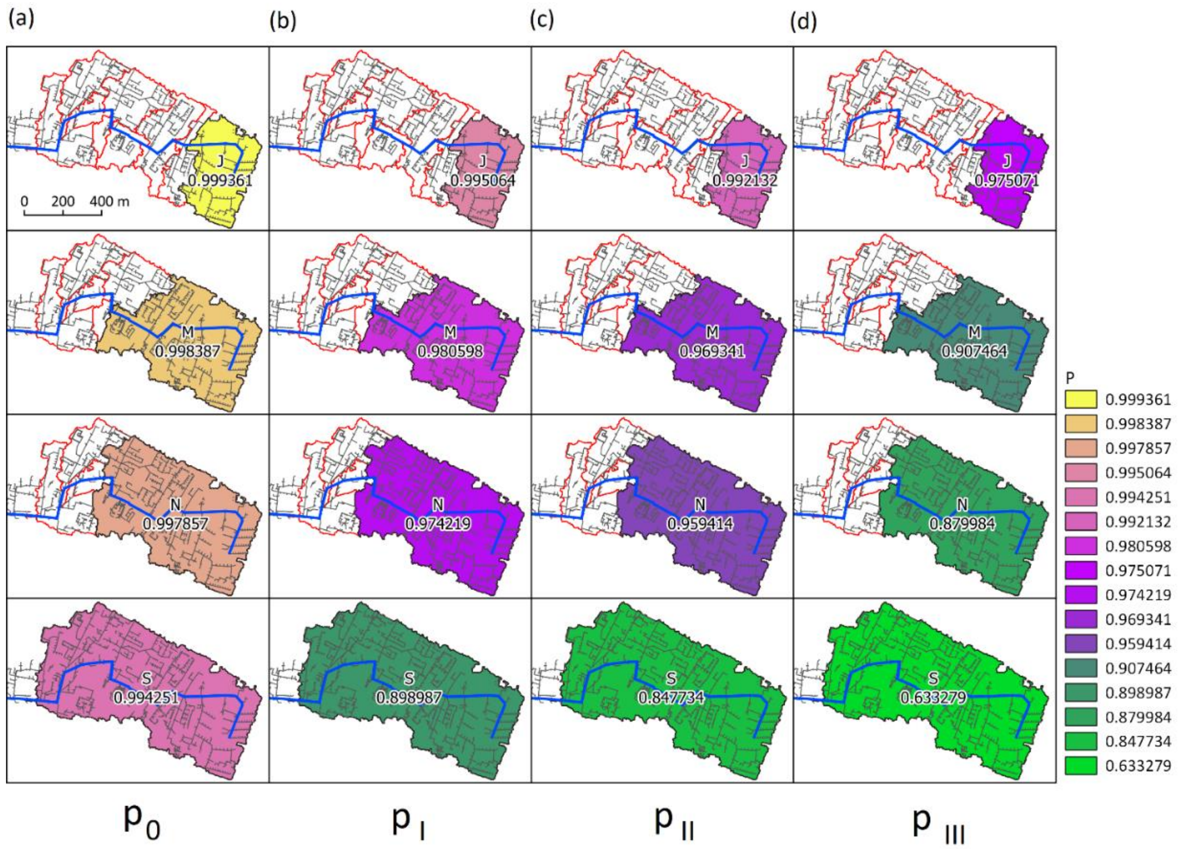


Figure 6. Probability of specific flood volume in sub-catchments for: (a) present state (p_0) and for (b) I, (c) II, (d) III corrective variants.

It was found that decrease of catchment imperviousness (variant I) leads to improvement of stormwater system operation, however it is related to catchment characteristics and stormwater network characteristics. It was indicated that decrease of Imp by 10% in sub-catchment J has negligible impact on p_m value, while in sub-catchment S it results in the decrease of specific flood volume probability by 10%. Greater impact of lower hydraulic load was observed for variant II, where reduction of p_m by 1% for sub-catchment J and by 15% for sub-catchment S was obtained. The greatest improvement of stormwater network operating was obtained in case of variant III, when p_m value decreased by 2% and 36% for sub-catchments J and S, respectively odpowiednio o 2% i 36%. After analysis of the change of p_m values in sub-catchments J, M, N, S for corrective variant III, it was found out that despite enhancing retention depth and channel capacity while reducing catchment imperviousness, hydraulic overloads (κ = 13 $m^3 \cdot ha^{-1}$) still occur in the analysed catchment. This indicates the need for further changes in both the catchment area and stormwater network. For variants I, III the Imp values for the sub-basin are below the applicability range of the logit model, therefore in order to verify the results obtained hydrodynamic model simulations were performed (Tab. 3S).

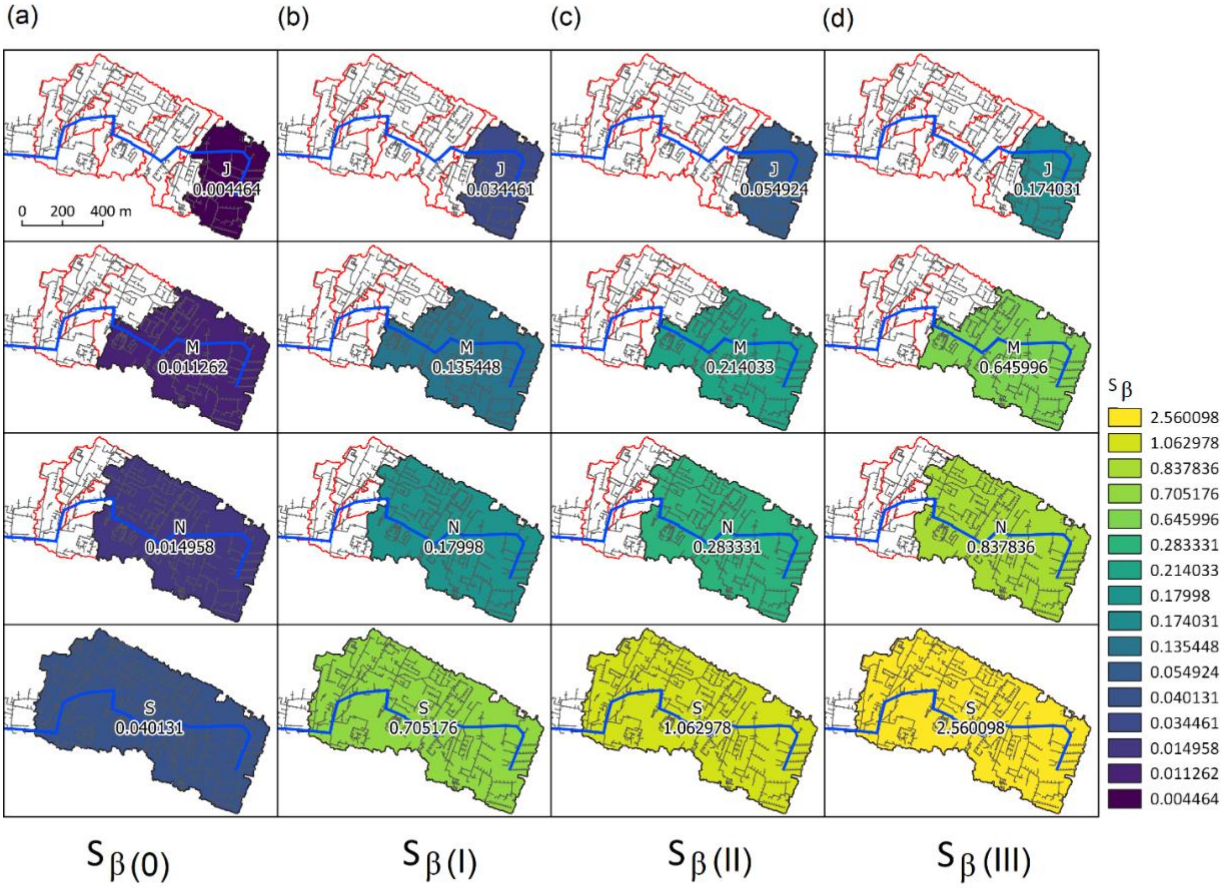


Figure 7. Sensitivity coefficient (S_β) in sub-catchments for: (a) present state (0) and for (b) I, (c) II, (d) III corrective variants.

The results of the model calculations confirm their high agreement; out of 72 cases, identical results were obtained in 68. In addition to these calculations, the variability of sensitivity coefficients (S_β) in sub-catchments for corrective variants I, II and III was also analysed (Fig. 7). It was proved that decrease of catchment imperviousness results in greater impact of β on specific flood volume (Fig. 7). For catchments J, S decrease of Imp by 10% (variant I) led to decrease of S_β value by 7.55 times and 17.50 times, for catchments J, S, respectively. In case of variant II (increased catchment retention) it was found that sensitivity coefficients are higher than 51% (sub-catchment S) and 59% (sub-catchment J). The highest S_β values for sub-catchments J and S were obtained in variant III. Obtained results (Fig. 7) confirmed high variability of S_β depending on catchment characteristics and stormwater network characteristic for all analysed variants. It was indicated that S_β values for sub-catchment S are higher than in sub-catchment J by 20.7 times, 19.3 times and 14.7 times for variants I, II, and III, respectively. These results provide relevant information for planning retention infrastructure that reduces outflow – for instance, Green Infrastructure (GI) facilities. They also point out the need to widen the range of applicability of proposed simulator as well as for including parameters referring to GI, which would allow for planning of their location inside analysed catchments.

Review 7

This made the Section of conclusion weak as well; e.g., the authors conclude "no other previous study has included such a broad scope of analysis" (line 550), however they adopted their previous work and presented similar results here providing similar messages and interpretation.

Response 7

Dear Reviewer, Thank you for your comment. Considering the above remarks (Response 1, 2), we can state that the simulation results obtained in this manuscript are original. In the planned correction, we plan to highlight the differences between the models developed so far and the model proposed in this paper in tabular form. Much more attention has been paid to the influence of rainfall data, characteristics (catchment, sewer network) on the results of sensitivity analysis in the context of literature data. The advantages and disadvantages of the sub-basin delineation adopted for the calculations are highlighted. Planned revisions to the manuscript are listed below.

Developing and calibrating mathematical models to simulate stormwater network operation under hydraulic overloads is one of the latest areas of research. In comparison to the statistical models used so far (Li and Willems, 2019; Thorndahl 2009), the approach proposed in our study includes SWMM model parameters describing catchment retention and, at the same time, the characteristics of the catchment and stormwater network (tab. S4). Apart from the model developed in this study, the above mentioned factors are only included in mechanistic models, which have a form of differential equations. Therefore, they require a large number of simulations in order to determine the impact of selected variables on computation results of specific flood volume. Models developed with machine learning methods are free of such drawbacks (tab. S4), which have a form of empirical relationships. In contrast, in case of models developed with neuron networks, there is a need of performing additional analyses (Ke et al., 2020; Yang et al., 2020). Jato – Espino et al. (2018, 2019) and Li and Willems (2020) analysed stormwater flooding from manholes based on catchment characteristics and stormwater network characteristics (tab S4). Szeląg et al. (2022) confirmed their results and developed a model for identification of stormwater flooding in a catchment. Besides, by indicating the impact of uncertainty of SWMM model parameters on stormwater flooding, Szeląg et al. (2021) proved that previous approaches require further development. In the wider context of catchment management, their approach does not apply for the characteristic of the materials used for road, roofs or parking places, etc. Fu et al. (2011) and Thorndahl et al. (2009) analyzed the uncertainty of the identified parameters, which allowed, for example, to correct for impervious area retention, roughness coefficient without being able to correct for catchment imperviousness, which limited the use of the models in catchment management. The approach proposed in our study is a combination of these two solutions, which provides a tool which can be successfully implemented to manage other catchments.

The results of our study confirmed the major significance and huge interaction between catchment characteristics and SWMM model parameters. This fact can be further compared by several references (Li and Willems, 2020; Jato – Espino et al., 2019; Zhuo et al., 2019) presenting comparisons of flooding simulations in urban catchments.

Tab. S4. Comparison of developed model for identification of specific flood volume to literature data

Study	Criteria	M	I	R	C	S	P
Duncan et al. (2011)	occurence of flooding	✓	•	✓	✓	✓	•
Jato - Espino et al. (2018)	occurence of flooding	✓	✓	✓	✓	✓	•
Jato - Espino et al. (2019)	occurence of flooding	✓	•	✓	✓	✓	•
Li and Willems (2020)	occurenceof flooding	✓	✓	✓	✓	✓	•
Szeląg et al. (2022)	occurence of flooding	✓	✓	✓	✓	✓	✓
Szeląg et al. (2021)	volume	•	•	✓	✓	✓	✓
Thorndahl et al. (2008)	volume	✓	✓	✓	•	✓	✓
Verbovski et al. (2022)	volume	✓	✓	✓	•	•	•
Fu et al. (2011)	volume	•	•	✓	✓	✓	✓
Chen et al. (2020)	volume	•	•	✓	✓	✓	✓
Fraga et al. (2016)	volume	•	•	✓	✓	✓	✓
this study	volume	✓	✓	✓	✓	✓	✓

where: M (method); the models were divided into two groups: mechanistic (·) and machine learning (ᐯ); R (rainfall); C (catchment); S (sewer); P (calibration parameter); I (interpretation model, based on estimated factors the impact of analysed factors on stormwater flooding can be determined).

Our analysis indicated that an impervious area in a catchment (Imp, Impd) leads to the increase of flooding; reverse dependency was obtained by Jato – Espino et al. (2018) when modelling flooding from manholes. Increase in channel volume above the closing cross-section of a catchment (Vk) and its longitudinal slope (Jkp) results in the decrease of flooding, that was confirmed by computations performed for Espoo catchment in Finland (Jato – Espino et al. 2019). Interestingly, the increase of unit impervious area per the length of main stormwater interceptor (Gk, Gkd) results in smaller volume of stormwater flooding. This result is absolutely right due to the fact that the longer the channel, the greater the number of manholes. Huang et al. (2018) based on observations conducted in a complex stormwater system indicated the impact of catchment location and hydrological conditions on the maximum outflow. Yao et al. (2019) obtained similar results after computations with a mechanistic model for catchments in Beijing and in Dresden (Reyes – Silva et al. 2020).

Calculation results obtained in this study confirmed relevant impact of rainfall data, catchment characteristics, and stormwater network characteristics on sensitivity coefficients – relationships between SWMM parameters and specific flood volume. For rainfall data and catchment characteristics (assumed as constant) it was proved that correction coefficient of impervious area (β) and the Manning roughness coefficient for channels (n_{sew}) have the greatest impact on specific flood volume. The results of our computations are consistent with Thorndahl et al. (2009), who simulate flooding from a single manhole in the Frejlev catchment (Belgium), based on rainfall data and calibrated parameters of a hydrodynamic model. These findings were confirmed by calculations Fu et al. (2012) and Prodanovic et al. (2022) respectively for catchments of 400 ha and 8 ha. Szeląg et al. (2021) based on simulations with mechanistic model including uncertainty of SWMM parameters proved the key impact of Manning roughness coefficient of sewers on specific flood volume (for rainfall episoed t_r = 30 min and P_t = 15.25 mm). Fraga et al. (2016) used GLUE+ GSA method for a small road catchment and indicated the impact of rainfall data (rainfall duration, depth, temporal distribution) on sensitivity analysis results. I was further confirmed in computations of stormwater flooding using logit model (Szeląg et al. 2022) and specific flood volume calculations with SWMM model (Freni et al. 2012). Xing et al. (2021) used mechanistic model to determine characteristics of spatial development and stormwater characteristics in Chongqing catchment (China) on the depth of stormwater flooding. The aforementioned research studies indicate the impact of rainfall data, catchment characteristics, and stormwater network characteristics on sensitivity of hydrodynamic simulation model for stormwater flooding.

Differences in probability of specific flood volume/sensitivity coefficients indicate the influence of catchments downstream on conditions in the catchment above. The variation in sensitivity coefficients does not account for local conditions within the side channels. Due to the creation of successive sub-catchments by combining them, the conditions of the sewer system in its area are averaged out, making the interpretation of the results difficult. Using the developed tool, catchment management may become difficult when there is a particularly hydraulically overloaded area within the catchment, which impacts neighboring sub-catchments.