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Automated modelling of urban runoff based on domain knowledge and equation discovery

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ABSTRACT

Modelling tools are widely used to analyse the urban drainage systems and to simulate the effects of future urban development and stormwater control measures. Usually, these tools use only one mathematical model (predetermined by the modeller) at a time to describe a single hydrological process within the urban catchment. When there are alternative mathematical models for describing the same hydrological process, their suitability needs to be investigated separately, which makes the modelling task even more complex, time consuming and open for human errors. Furthermore, models have to be calibrated to achieve a better fit between measured and simulated runoff. Calibration can be performed either manually, by using a trial-and-error approach, or by employing search techniques and parameter optimization tools. To overcome the drawbacks associated with manual selection and calibration of models, automated modelling based on equation discovery was used in this study to a) find the most suitable mathematical model among multiple alternatives for describing every (environmental) process modelled and b) to calibrate the model parameters against measured data. First, knowledge on urban runoff modelling was formalized into a new library of modelling components, compliant with the equation discovery tool ProBMoT (Process Based Modelling Tool). Next, a conceptual model of the experimental urban sub-catchment within the city of Ljubljana, Slovenia, was defined. ProBMoT was used to find the structure and parameters' values of alternative rainfall-runoff models, according to the defined conceptual model that provide optimal fit against pipe flow measurements. Three alternative methods were used to describe infiltration: the SCS CN method, the Variable UK runoff equation, and the UK Water Industry Research equation. The proposed automated model discovery approach for finding the optimal rainfall-runoff model proved to be very efficient. Nine rainfall-runoff models were created with very good performance. The best performance was achieved by the models that used a combination of two different infiltration methods, i.e. the SCS CN infiltration method for the pervious area and one of the other two infiltration methods for the impervious area.

1. Introduction

Growing urbanization, combined with climate change bringing more frequent and intensive rain events, is putting additional pressure on existing urban drainage (UD) systems (Zhou, 2014). Consequently, these systems frequently fail to effectively perform their function. Therefore, modelling and decision support tools can be of great assistance for analysing the current state of UD systems and for selecting the most suitable stormwater control measure(s) (SCMs) (e.g., Štajdohar et al., 2016; Zhu et al., 2019; Li et al., 2020). In this context, one of the most widely used hydrological-hydraulic models of urban catchments is the open-source Stormwater Management Model (SWMM) (Rossman, 2015), which supports a wide range of modelling functionalities, namely water quantity, water quality, sustainable drainage devices and spatial planning (Zoppou, 2001; Zhou, 2014).

However, SWMM does not provide: a) geographic information system (GIS) functionalities, such as catchment discretization, b) detailed overland routing simulations, and c) parameter calibration. Thus, in recent years, researchers have tried to overcome these limitations by proposing solutions that would to some extent automate or formalize the

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model development process within SWMM. Allende-Prieto et al. (2018) and Radinja et al. (2019) have developed urban hydrological-hydraulic models by using the open-source software Giswater (Giswater Association, 2015), which enables integration of geospatial data (i.e., sewer system network, DEM, etc.) into the model development process. Furthermore, Dongquan et al. (2009) have successfully applied automatic GIS-based catchment discretization on a Macau case study area of 13.65 ha. Similarly, Warsta et al. (2017) have developed an automated subcatchment generator for SWMM using open data, which significantly accelerates project setup. The generator was applied to two subcatchments in Helsinki, with an area of 13.9 ha and 33.5 ha respectively. Younis et al. (2017) have employed automated processing of satellite images for land use classification to improve the calibration of a wastewater network.

To improve overland routing simulations, SWMM has been recently coupled with a two-dimensional overland flow model based on the cellular automata approach, for providing reliable urban nonpoint source pollution data (Dai et al., 2020). A similar approach has been used to simulate interactions between surface runoff and UD systems (Abbasizadeh et al., 2018).

SWMM, like any other mechanistic model, uses one mathematical model (predetermined by the modeller) at a time to describe a single hydrological process within the urban catchment. After initial simulation, models are calibrated to achieve a better fit between the measured and simulated runoff. Calibration can be performed either manually/iteratively by using a trial-and-error approach or by employing search techniques (e.g., genetic algorithms, neural networks, regression trees etc.) (Niazi et al., 2017; Hu et al., 2018) and parameter optimization tools (e.g., PEST, OSTRICH) (Perin et al., 2020; Shahed Behrouz et al., 2020). Optimization can be formulated either as a single-objective problem that minimizes the aggregate difference between measurements and model simulations or a multi-objective problem that considers multiple trade-offs (e.g., water quantity/quality, costs, and biodiversity) (di Pierro et al., 2006; Gamerith et al., 2011; Macro et al., 2019).

In case there are alternative mathematical models for describing the same (e.g., hydrological) process, their suitability needs to be investigated separately, which makes the modelling task even more complex, time-consuming and open for human errors. To overcome the drawbacks associated with manual calibration and manual selection of models, automated modelling (AM) based on equation discovery can be used to a) find the most suitable mathematical model among multiple alternatives for describing every (environmental) process modelled and b) to calibrate the model parameters against measured data.

Equation discovery is an area of machine learning that develops methods for automated discovery of mathematical models, expressed in the form of equations, from collections of measured data (Džeroski and Todorovski, 2008). Automated modelling using knowledge libraries of model components has been already successfully applied for modelling aquatic ecosystems (Atanasova et al., 2006), watersheds (Škerjanec et al., 2014), dynamic biological systems (Tanevski et al., 2016), and water-tank dynamics (Simidjievski et al., 2020). To the best of our knowledge, no such attempts have yet been made in the field of urban surface runoff modelling.

This paper provides integration of automated equation (model) discovery and domain-specific knowledge in the field of surface runoff modelling. More specifically, the main aims of the paper are to:

a) Develop a library of components formalizing the knowledge on urban runoff modelling, compliant with the equation discovery tool ProBMoT (Process-Based Modelling Tool) (Džeroski et al., 2020).

b) Define a conceptual model of the experimental urban subcatchment within the city of Ljubljana, Slovenia.

c) Apply the proposed automated model discovery approach to find the optimal rainfall-runoff model for the above-mentioned case study area that best fits the available pipe flow measurements.

2. Case study area

The case study area is located in the western part of the city of Ljubljana, Slovenia, and covers about 30 ha. The predominant land use in this area is family houses with gardens (Fig. 1). The typical climate for the area is a temperate continental climate. The mean long-term (1986 – 2016) annual rainfall is about 1380 mm and the average annual temperature is 11 °C, ranging from –3 °C in winter to 24 °C in summer (Slovenian Environment Agency, 2018). The largest part of the area is serviced by a mixed sewer system with a length of approx. 5.4 km.

3. Data and methods

3.1. Data

Precipitation data were provided by the Slovenian Forestry Institute,

Fig. 1. Case study area.

for a rain gauge station located on the north side of the case study area (location: 46°03′06.82″ N, 14°28′47.58″ E, 306 m a.s.l.) (Slovenian Forestry Insitute, 2019). The measurements were performed with a Davis® (0.2 mm) Rain Gauge Smart Sensor (Onset Computer Corporation, 2016). The local public utility company (JP VODOVOD KANALIZACIJA SNAGA d.o.o.) provided the information on the combined sewer network and the flow measurement data. The flow measurements were performed between 1 March 2019 and 30 September 2020 in a pipe (of the combined sewer system) collecting all contributing water from the case study area (location: 46°02′44.56″ N, 14°29′01.82″ E, 295 m a.s.l.) (Fig. 1). The flow rate was calculated based on the combination of non-contact radar velocity measurements and ultrasonic water level measurements (Raven-eye, 2020). As the focus was only on surface runoff (stormwater) modelling and the measurements were conducted in a combined sewer system, the dry weather flow, which was measured before each rain event (8 – 20 L/s), was deducted from the total measured flow. For the preparation of precipitation and flow data, a 5-minute time step was used.

Within the flow measurement period, four rainfall periods were selected for model calibration (C1 – C4) and four rainfall periods were selected for model validation (V1 – V4) (Table 1). Based on their duration, the rainfall periods can in general be divided into two groups: shorter (approx. 1 day) and longer (approx. 6 days). Hence, two short (C1 and C2) and two long (C3 and C4) rainfall periods were selected for model calibration. The longer calibration periods include multiple rainfall events of different intensities and durations, so that the ProBMoT tool could learn from different surface runoff responses of the catchment. The validation periods were selected based on the following criteria: a) duration, with shorter (V1 and V2) and longer (V3 and V4) periods; b) seasonal distribution; c) similarity in peak flows; d) stability of measured flows; and e) antecedent dry weather period. The rainfall periods are presented in consecutive order, based on the modelling phase (either calibration - C or validation - V) and duration of the modelled rainfall period (e.g. 1D – one day) (Table 1).

3.2. Rainfall-runoff model

Our rainfall-runoff model is based on the principles and equations used by the EPA Storm Water Management Model (SWMM)(Rossman, 2015). The catchment is represented as a nonlinear reservoir, governed by surface storage mass balance, i.e. conservation of mass:

$$\frac{\partial d}{\partial t} = i - f - q \tag{1}$$

where d is the surface storage [m], i is the rate of rainfall [m/s], f is the infiltration rate [m/s], and q is the runoff rate [m/s]. Evaporation was not included in the model, due to its limited potential to significantly influence the water cycle within the modelled rainfall periods. The runoff flow rate per unit of the surface area is based on Manning's equation (Rossman, 2015):

$$q = \frac{WS^{0.5}}{An}(d - d_s)^{5/3} \tag{2}$$

where q is the runoff flow rate per unit of the surface area [m/s], W is the sub-catchment width [m], S is the average slope of the sub-catchment [m/m], A is the surface area of the sub-catchment [m^2], n is the surface roughness coefficient [s/m$^{1/3}$], d is the ponded water [m], and d_s is the depression storage depth [m]. Afterwards, the total runoff flow from the catchment [L/s] is calculated by multiplying the catchment surface area [m^2] and q [m/s].

There are several well-known alternative methods for modelling the infiltration process. Three alternatives were considered in this study: the SCS CN method, the Variable runoff equation, and the UK Water Industry Research runoff equation. Thus, the complete rainfall-runoff model can have different structures based on which infiltration method is selected. In addition, different infiltration methods can be applied in different sub-catchments, resulting in many plausible model structures for a given catchment.

3.2.1. SCS CN method

This method assumes that the total infiltration capacity of a soil is related to the soil's tabulated Curve Number (CN). The CN value is determined based on the hydrologic soil group, land use and hydrologic condition. CN values range from 30 to 98. The latter value is assigned to paved roadways, roofs and other impervious surfaces. At higher CN values, precipitation is mainly translated into a runoff. On the other hand, at lower CN values rainfall is mainly infiltrated and is thus not translated into runoff (NRCS, 1986). A modified version of the SCS CN equation was used, as described in the SWMM Reference Manual - Hydrology (Rossman, 2015). In the modified version, the initial abstraction (I_a) is not included, as it is already included in the depression storage (d_s; see Eq. (2)). The following three equations (Eq. (3)–(5)) are used to calculate the infiltration rate:

Table 1
Characteristics of the selected rainfall periods used for calibration and validation.

Period ID	Rainfall period - start	Rainfall period - end	Duration [h]	Season	Total precip. [mm]	Total precip. time [h]	Average precip. intensity [mm/5min]	Antecedent dry weather period [h]	Total measured flow [m^3]	Measured peak flow [L/s]
C1_1D	1 Dec 2019 (23:00)	2 Dec 2019 (19:00)	20	Autumn	24.4	8.3	0.24	92	8,948	278
C2_1D	15 May 2020 (05:00)	16 May 2020 (03:00)	22	Spring	29.6	7.3	0.34	51	7,409	442
C3_6D	23 Apr 2019 (04:30)	29 Apr 2019 (04:30)	144	Spring	39.8	13.6	0.24	261	6,562	308
C4_7D	11 Nov 2019 (12:30)	18 Nov 2019 (11:30)	167	Autumn	74.4	25.3	0.25	57	20,938	555
V1_1D	31 Aug 2020 (12:00)	1 Sept 2020 (11:00)	23	Summer	20.8	7.8	0.22	17	5,417	238
V2_2D	21 Dec 2019 (08:00)	23 Dec 2019 (02:00)	42	Winter	56.4	14.3	0.33	115	17.045	429
V3_5D	28 Sept 2019 (12:00)	3 Oct 2019 (01:00)	109	Autumn	38.8	8.5	0.38	60	7.854	283
V4_5D	1 Mar 2020 (07:00)	6 Mar 2020 (15:00)	128	Winter	81	26.1	0.26	55	19,578	301

$$f = \frac{(F_2 - F_1)}{\Delta t} \tag{3}$$

where f is the infiltration rate [m/s], F_2 is the cumulative infiltration at the end of a time step Δt [m], F_1 is the cumulative infiltration at the beginning of a time step Δt [m], and Δt is the time step [s];

$$F = P - \left(\frac{P^2}{P + S_{max}}\right) \tag{4}$$

where F is the cumulative infiltration [mm], P is the cumulative precipitation [mm], and S_{max} is the maximum storage capacity of a soil [mm];

$$S_{max} = \left(\frac{1000}{CN} - 10\right) \times 25.4 \tag{5}$$

where S_{max} is the maximum storage capacity of soil [mm] and CN is the tabulated coefficient that varies with the land use and soil type.

3.2.2. Variable UK runoff equation

The Variable UK runoff equation (VARUK) has three components: runoff from impervious areas, runoff from pervious areas and initial losses (Butler et al., 2018). It is based on data from 11 UK catchments and 112 rain events. The VARUK equation is as follows (Packman, 1990):

$$PR = IF \times PIMP + (100 - IF \times PIMP)\frac{NAPI}{PF} \tag{6}$$

where PR is the percentage runoff, IF is the effective impervious area factor, $PIMP$ is the percentage of imperviousness, $NAPI$ is the antecedent precipitation index [mm], and PF is the porosity factor [mm].

The rainfall can be converted into infiltration by using the following equation:

$$f = i \times \left(1 - \frac{PR}{100}\right) \tag{7}$$

3.2.3. UK water Industry Research runoff equation

The UK Water Industry Research runoff equation (UKWIR; Kellagher, 2014) was developed to overcome some of the limitations of VARUK (Woods Ballard et al., 2015), which are described in detail in the report Development of the UKWIR Runoff Model (2014). As VARUK, it has a fixed runoff component for paved surfaces ($IF_n \times PIMP_n$). It was upgraded with a variable runoff component for paved surfaces$(1 - IF_n) \times PIMP_n$. Additionally, a component for pervious surfaces was added$(1 - PIMP_{TOTAL})$, which enables differentiation between winter and summer runoff (i.e. negative NAPI). The UKWIR equation is then as follows:

$$PR = \sum_{n=1}^{N}\left(IF_n \times PIMP_n + (1 - IF_n) \times PIMP_n \times \frac{PI_{pv}^{\beta}}{PF_{pv}}\right) + \left((1 - PIMP_{TOTAL}) \times \frac{(NAPI_s + PI_s)^{Cr} \times SPR}{PF_s}\right) \tag{8}$$

where PR is the percentage runoff for the model, IF_n is the effective impermeability factor for a particular paved surface type, PI_{pv} is the precipitation index for paved surfaces with a rapid decay coefficient, β is the power coefficient for paved surface, PF_{pv} is the soil store depth for paved surface [mm], $NAPI_s$ is the antecedent precipitation index for a particular pervious surface type, PI_s is the precipitation index for pervious surface with a decay coefficient, Cr is the power coefficient for pervious surface, SPR is the standard percentage runoff, and PF_s is the soil storage depth for a particular pervious surface type [mm].

3.3. Equation discovery and process-based modelling

The proposed automated modelling approach is based on the Process-Based Modelling Tool (ProBMoT), developed by Čerepnalkoski et al. (2012). ProBMoT allows for the integration of domain knowledge (e.g., urban hydrology), formalized as template components for the construction of the process-based models, into equation discovery from measured data. It automatically identifies both the structure and parameter values of an appropriate process-based model, given: a) a knowledge library (i.e., a mathematical formulation of the selected domain) in the form of model components, or, more specifically, template entities and processes, b) a conceptual model of the observed system, and c) measurements (Fig. 2).

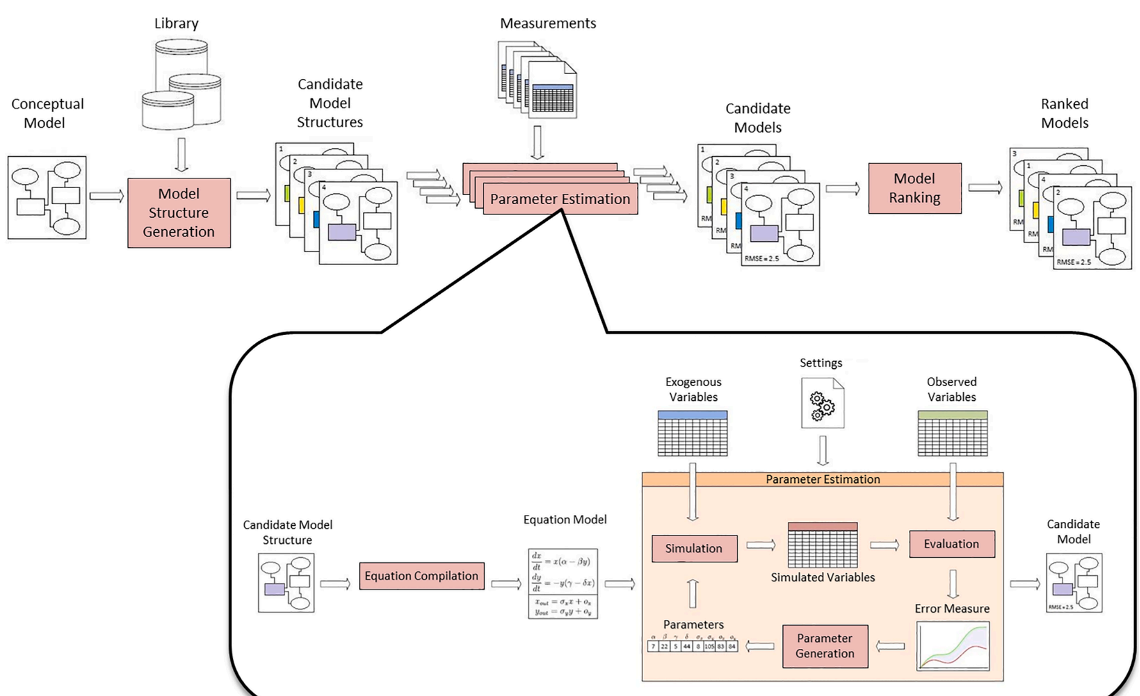

Fig. 2. A schematic workflow for the automated modelling tool ProBMoT (Škerjanec et al., 2014).

Candidate model structures are generated from the knowledge library and a user-specified conceptual model of an observed system. The candidate models are transformed into equations, calibrated against measurements and ranked according to their errors. The latter are calculated as the root-mean-squared-error (RMSE), i.e. discrepancy between the model simulation and measured data.

To use ProBMoT for rainfall-runoff modelling in the presented case study, the following steps were taken: (1) the rainfall-runoff methods were encoded in a modelling library, (2) a conceptual model of the case study was elaborated, and (3) ProBMoT was set to discover the best model structure and parameters following the conceptual model of the case study (Radinja et al., 2021).

3.3.1. Library of components for modelling rainfall-runoff

The library consists of entity templates, process templates, and compartment templates. Each template captures general knowledge that applies to different cases and can be reused when dealing with a specific task. The dynamic system to be modelled, i.e., the catchment, can be structured by using compartments. Compartments are organized in a nested, tree-like structure. Each compartment contains entities and processes and can also contain other sub-compartments (e.g., sub-catchments or functional units) (Škerjanec et al., 2014).

Moreover, entities represent the actors of the observed system. These actors are involved in processes that explain how entities interact, as well as what is the influence of the interactions on the involved entities themselves. In the urban runoff-modelling domain, entities correspond to different pools within the urban water cycle, climate variables and various types of constituents.

Finally, processes provide quantitative descriptions of the relations among entities, in terms of one or more equations. In the urban runoff-modelling domain, examples of processes include water fluxes, i.e., transfer processes that are involved in the water cycle (e.g., surface runoff, infiltration) (Fig. 3). Thus, processes calculate the change of water fluxes (e.g., surface storage) within a time step and entities aggregate these changes over the simulated time.

The equations presented in Section 3.2 were encoded in the knowledge library as template processes named Hydrological processes. These include Outflow, SurfaceStorage, SurfaceRunoff, and Infiltration, with three alternative methods: InfiltrationSCS, InfiltrationUKWIR, and InfiltrationVARUK. Additionally, the Intercompartmental process TotalOutflow was introduced to sum the Outflow from both sub-compartments (i.e., sub1 and sub2; see Radinja et al., 2021). The time step in the presented equations is 1 s, thus ProBMoT is calculating the infiltration rate in m/s and flow in L/s. However, the actual time step of the input data (e.g., precipitation, measured flow) is 5 min, thus this is also the reporting time step.

3.3.2. Conceptual model of the case study area

The conceptual model of the case study area (Fig. 1) was structured as a single compartment (i.e., catchment), divided into two sub-compartments (i.e., sub1 and sub2). Sub1 represents the impervious part of the catchment and sub2 the pervious part of the catchment (Fig. 3).

First, the parameters that appear in the equations presented in Section 3.2 were listed as constants within the template entity Surface in the knowledge library, together with their expected ranges and units. Afterwards, this template was reused within the conceptual model (see Radinja et al., 2021), where the values and ranges of the constants were adjusted based on the (im)perviousness of the sub-catchment (Table 2), following the values proposed in the literature (NRCS, 1986; Kellagher, 2014; Rossman, 2015).

Table 2
Values/ranges assigned to each constant, for sub-catchments sub1 and sub2 (conceptual model, entity Surface).

Constants	Unit	sub1 - impervious	sub2 - pervious
area	m^2	150,000	150,000
slope	m/m	0.002	0.002
width	m	range: 5000 – 10,000	range: 5000 – 7,500
depstordepth	m	range: 0.00005–0.001	range: 0.0005–0.006
n	$s/m^{1/3}$	range: 0.01–0.08	range: 0.15–0.80
CN		range: 90–99	range: 30–75
PIMPimp		100	0
IF		range: 0.5–1	/
B		range: 0.5–0.8	/
PIimp		range: 0–1	/
PFimp	mm	range: 10–15	/
PIMPp		100	0
NAPI	mm	/	range: 0–40
PIp		/	range: 0.7–0.9
Cr		/	range: 0.8–1.0
SPR		/	range: 0.1–0.7
PFp	mm	/	range: 30–50

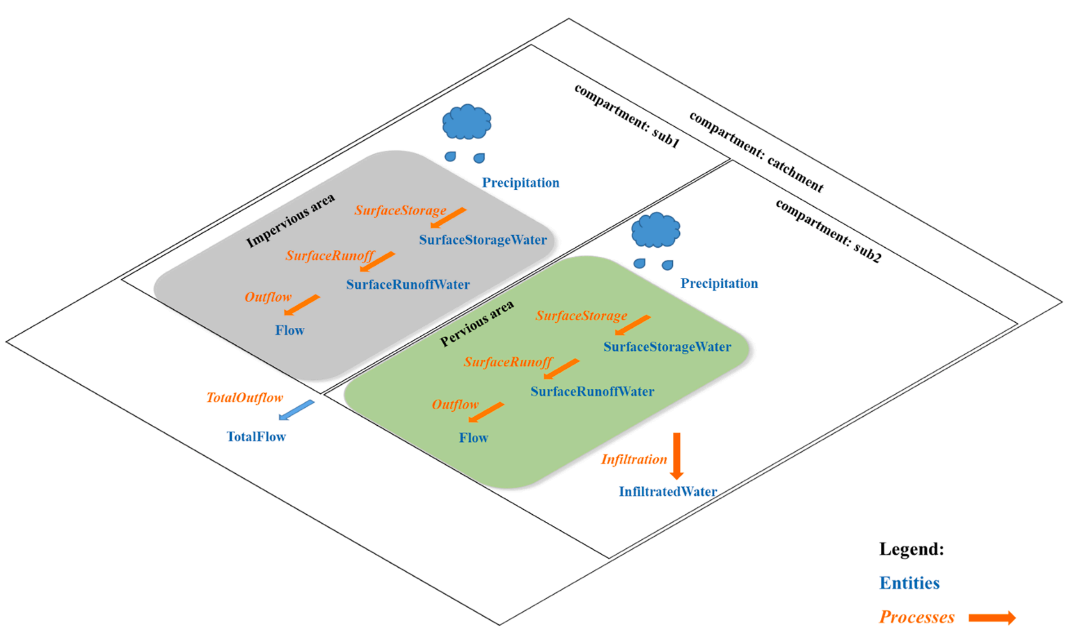

Fig. 3. Conceptual model of the structured urban catchment – compartments, entities and processes.

3.4. Assessment and comparison of model performance

Once the potentially viable model structures are composed by the ProBMoT algorithm, their parameters are fitted to the provided measurements and the resulting models are assessed according to their goodness of fit. Two measures are used to assess model performance: the Nash-Sutcliffe efficiency coefficient (NSE) (Nash and Sutcliffe, 1970) and RMSE-observations standard deviation ratio (RSR) (Moriasi et al., 2007). NSE is commonly used to evaluate the goodness of fit of hydrological models. It can range from minus infinity to one, where one represents a perfect match between the observed and the modelled discharge. A value of 0 indicates that the observed mean is as good predictor as the model, while the negative values indicate that the observed mean is a better predictor than the model (Wilcox et al., 1990; Legates and McCabe, 1999). RSR is standardizing the RMSE (root mean square error) by using the standard deviation of observations. It can range from the optimal value of 0, which indicates a perfect model, to a large positive value indicating a corresponding error. The lower the RSR, the better the model performance. To rate model performance based on NSE and RSR, the categorization proposed by Moriasi (2007) was used (Table 3).

Table 3
Performance rating for models based on their NSE and RSR values (adopted from Moriasi et al., 2007).

Performance rating	NSE	RSR
Very good	$0.75 < NSE \leq 1.00$	$0.00 < RSR \leq 0.50$
Good	$0.65 < NSE \leq 0.75$	$0.50 < RSR \leq 0.60$
Satisfactory	$0.50 < NSE \leq 0.65$	$0.60 < RSR \leq 0.70$
Unsatisfactory	$NSE \leq 0.50$	$RSR > 0.70$

To find similarities/differences between the models based on their scored NSE and RSR values, the method of hierarchical clustering, as implemented by the Orange software (Demšar et al., 2013) was applied to the models. It forms a dendrogram for arbitrary types of objects (in this case models) based on a matrix of distances. Distances were calculated using the Euclidian metric, which is the “ordinary” straight-line distance between two points in Euclidean space. The points to cluster are the models, represented by their NSE and RSR values over all events (calibration and validation). For a better presentation of the hierarchical clustering, so-called heat maps were used to visualize the errors of the models with coloured spots.

4. Results

4.1. Calibration

Given the conceptual model and the modelling library, ProBMoT explored 9 alternative structures (M1 – M9) (Table 5), each of which was calibrated and validated against the measured data. All models were calibrated by simultaneously using data from two short time periods of

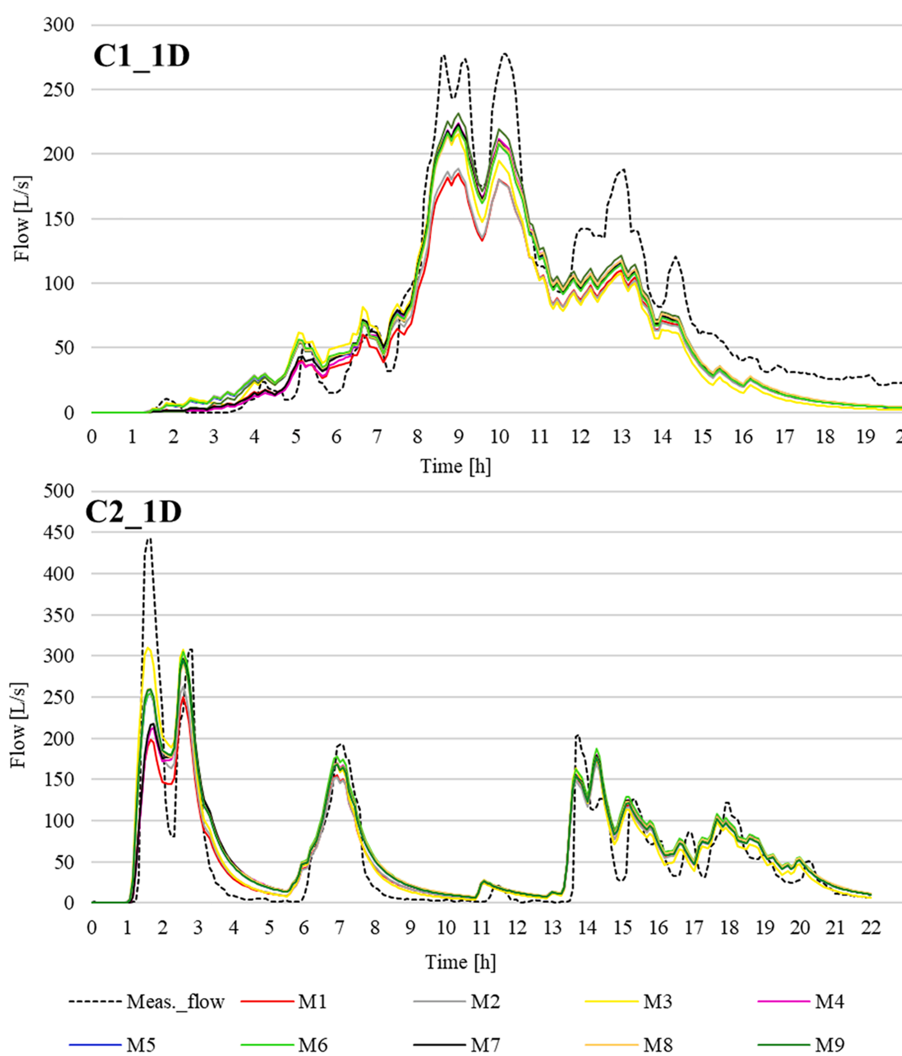

Fig. 4. The measured flow and model predictions for the calibration periods C1 and C2.

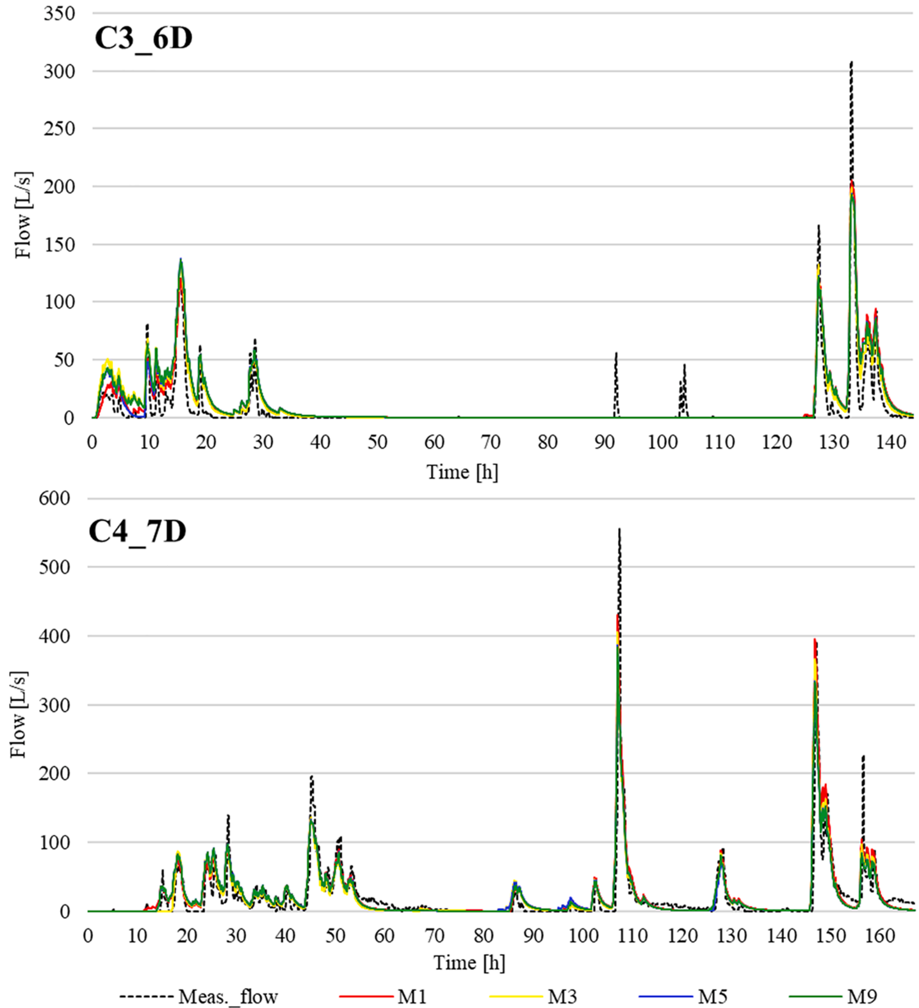

Fig. 5. The measured flow and the predictions of four models for the calibration periods C3 and C4.

Table 4
NSE and RSR values for all models and modelled rainfall periods.

Model	Infil. Sub 1	Infil. Sub 2	C1_1D		C2_1D		C3_6D		C4_7D		V1_1D		V2_2D		V3_5D		V4_5D	
			NSE	RSR	NSE	RSR	NSE	RSR	NSE	RSR	NSE	RSR	NSE	RSR	NSE	RSR	NSE	RSR
M1	SCS	SCS	0.79	0.46	0.72	0.55	0.78	0.47	0.77	0.48	0.83	0.41	0.91	0.31	0.86	0.37	0.75	0.50
M2	UKWIR	SCS	0.79	0.46	0.79	0.45	0.77	0.48	0.79	0.46	0.89	0.33	**0.92**	**0.29**	**0.87**	**0.35**	0.79	0.46
M3	VARUK	SCS	0.82	0.42	**0.82**	**0.42**	**0.78**	**0.47**	0.77	0.48	**0.94**	**0.25**	0.91	0.29	0.85	0.38	0.81	0.43
M4	SCS	UKWIR	0.89	0.34	0.72	0.55	0.73	0.52	0.79	0.46	0.88	0.34	0.89	0.34	0.77	0.48	0.80	0.44
M5	UKWIR	UKWIR	0.87	0.36	0.77	0.48	0.74	0.51	0.79	0.46	0.90	0.31	0.90	0.32	0.79	0.46	0.82	0.43
M6	VARUK	UKWIR	**0.90**	**0.32**	0.76	0.48	0.71	0.54	0.79	0.46	0.90	0.32	0.88	0.35	0.76	0.49	0.77	0.48
M7	SCS	VARUK	0.88	0.34	0.72	0.54	0.73	0.52	**0.79**	**0.45**	0.89	0.33	0.89	0.33	0.78	0.47	0.81	0.44
M8	UKWIR	VARUK	0.88	0.35	0.77	0.47	0.72	0.53	0.79	0.46	0.90	0.32	0.89	0.33	0.80	0.45	0.81	0.44
M9	VARUK	VARUK	0.87	0.36	0.78	0.47	0.73	0.52	0.79	0.46	0.91	0.30	0.90	0.32	0.81	0.44	**0.82**	**0.42**
Average:			0.85	0.38	0.76	0.49	0.74	0.51	0.79	0.46	0.89	0.32	0.90	0.32	0.81	0.43	0.80	0.45

measured flow, with a duration of approximately one day (C1 and C2) (Fig. 4), and two long time periods of measured flow, with a duration of approximately one week (C3 and C4) (Fig. 5). After calibration, all models generally had »very good« performance in terms of comparison between the simulated and measured flow (Table 4). For the first calibration period (C1), the models scored the following average grades; average NSE value of 0.85, and average RSR value of 0.38. However, the models that use the SCS CN infiltration method for the pervious area (M1 – M3) (average NSE value of 0.80) underpredicted the flow, when compared to the rest of the models (M4 – M9) (average NSE value of 0.88). For the second calibration period (C2), the models scored an average NSE value of 0.76, and an average RSR value of 0.49. However, the models that use the SCS CN infiltration method for the impervious area (M1, M4, M7) (average NSE value of 0.72) underpredicted the flow, when compared to the rest of the models (average NSE value of 0.78).

To improve the readability, only four models are presented on the hydrograph for longer calibration periods (C3 – C4) (Fig. 5). For the third calibration period (C3), the models scored an average NSE value of 0.74, and an average RSR value of 0.51, almost fulfilling the criteria for »very good« model performance. In comparison to the first calibration period (C1), the models that use the SCS CN infiltration method for the pervious area (M1-M3) (average NSE value of 0.78) performed better than the rest of the models (M4 – M9) (average NSE value of 0.73). For the fourth calibration period (C4), the models scored the average grades of 0.79 for NSE, and 0.46 for RSR. In comparison to the first three calibrations periods, no clear differences in model performance can be observed.

4.2. Validation

The calibrated models were validated on four different rainfall periods (Table 4) that vary in rainfall duration and intensity (Table 1). Fig. 6 presents the shorter two periods, namely V1, and V2. The validation period V1 lasted 23 h, i.e. 31 August 2020 (12:00) – 1 September 2020 (11:00), with an average measured flow of 39 L/s. For this validation period, the models scored an average NSE value of 0.89 and an average RSR value of 0.32. However, the model that only includes the SCS CN infiltration method (M1) performed worse than the rest of the models (i.e., its NSE is 0.07 lower). It underestimated the flow values for the (beginning of the) first rain event for both short validation periods (V1 and V2). The validation period V2 lasted for 54 h (2 days), i.e. from 21 December 2019 (08:00) – 23 December 2019 (14:00), with two rainfall events, causing the first and the second-highest peak flows among all validation events (Q_1 = 429 L/s, and Q_2 = 340 L/s). No clear differences in model performance can be observed across the different models for this validation period.

To improve the readability, only four models are presented on the hydrograph for the longer validation periods (V3 and V4) (Fig. 7). Namely, the three models that use the same infiltration method for the pervious and impervious area (M1, M5, M9), and model M3, which had the best performance for these validation periods (Fig. 7).

The validation period V3 lasted for 109 h (5 days), i.e. from 28 September 2019 (12:00) – 3 October 2019 (01:00), with two individual rainfall events. In this case, the models that use the SCS CN infiltration method for the pervious area, performed better than the other models, with an average NSE value of 0.86. The models that use the VARUK or UKWIR infiltration method for the pervious area scored lower NSE values, ranging between 0.76 and 0.81. The first rainfall event is very dynamic and consists of three sub-peaks (Q_1 = 185 L/s, Q_2 = 227 L/s, Q_3 = 260 L/s) within a period of 2 h, with clear breaks (low values) in-between (Q_1 = 51 L/s, Q_2 = 15 L/s). As for the previous validation periods, M1 underestimates flow at the beginning of the first event; however, it already fits the third sub-peak well. On the other hand, the models M3, M5, and M9 fit sub-peaks better; however, they do not fit the low values in-between as well. The second rainfall event also consists of three sub-peaks; here all models follow the shape of the measured hydrograph more consistently.

The validation event V4 lasted for 128 h (5 days), i.e. from 1 March 2020 (07:00) – 6 March 2020 (15:00), with three individual rainfall events (Fig. 7). For this validation period, the models scored an average NSE value of 0.80 and an average RSR value of 0.45. In general, all models overestimated the flow values. However, the model that only includes the SCS CN infiltration method (M1) performed worse than the rest of the models (i.e., its NSE is 0.05 lower). In comparison to the rest of the models, it least overestimated flow values for the (beginning of the) first rain event, yet for the next rain events, it overestimated flow

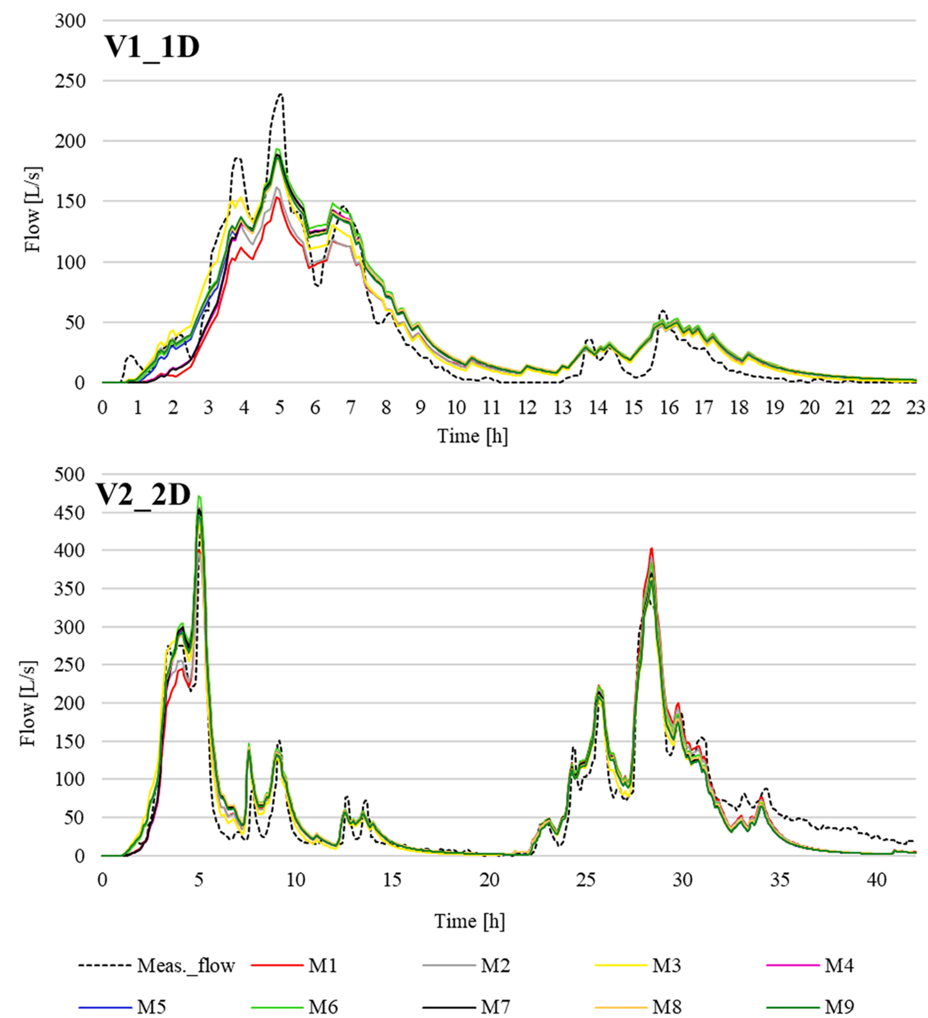

Fig. 6. The measured flow and model predictions for the validation periods V1 and V2.

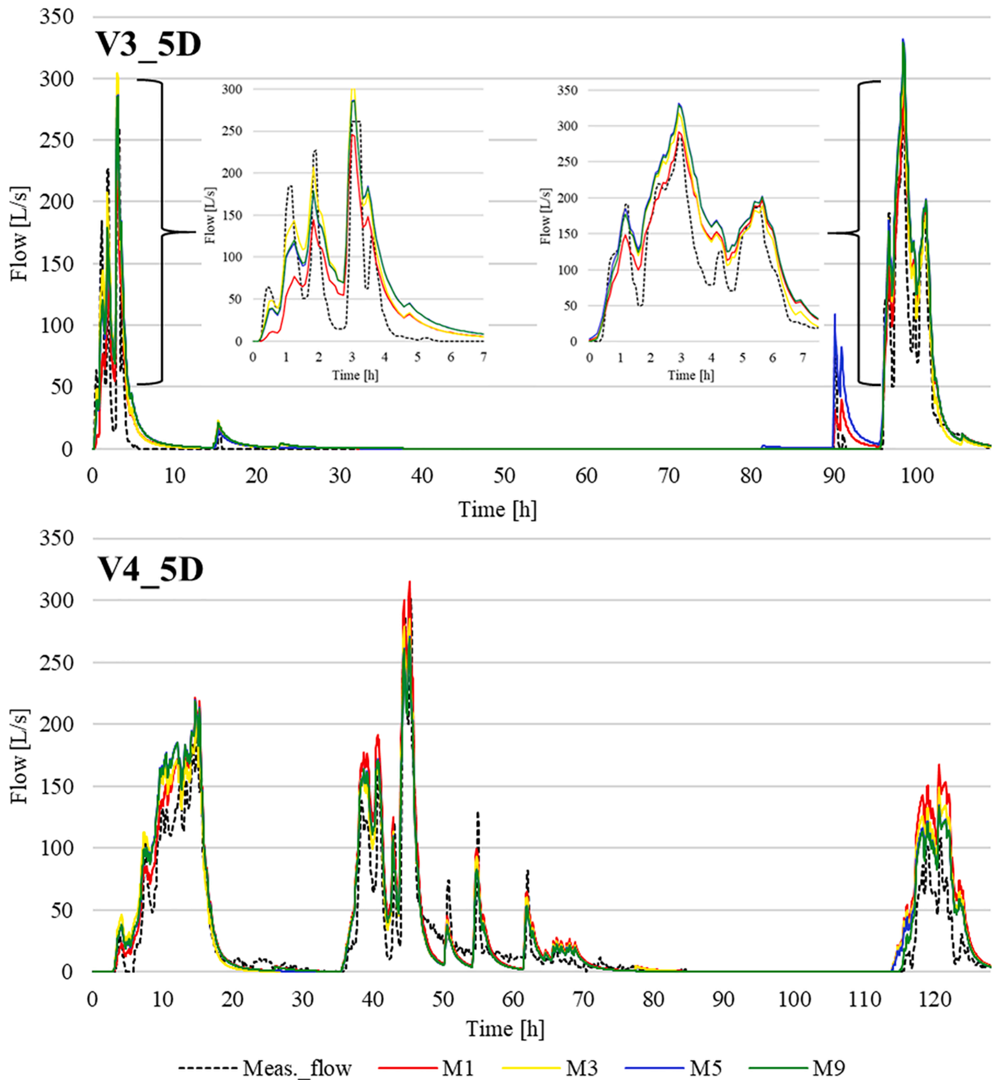

Fig. 7. The measured flow and the predictions of four models for the validation periods V3 and V4.

the most.

Using hierarchical clustering, we clustered the models into groups according to their performance profiles (in terms of NSE and RSR coefficients) across all calibration and validation periods (Fig. 8). One can notice that for both coefficients, models are clustered similarly. Models M1, M2, and M3 form the first group (G1); They all use the SCS CN infiltration method for the sub2 (i.e., pervious area). The rest of the models (M4 – M9) form the second group (G2). Furthermore, one can notice that the models in the first group (G1) are generally more heterogeneous than models in the second group (G2).

If we compare these groups based on the NSE and RSR values, one can notice, that for the shorter calibration periods (C1 and C2) models from the second group (G2) generally performed slightly better (i.e., average NSE 0.82, average RSR 0.42) than models from the first group (G1) (i.e., average NSE 0.79, average RSR 0.46). However, due to the very different model performance between M1 (i.e., NSE 0.83) and M3 (i.e., NSE 0.94) for V1, this observation is not confirmed for the short validation periods. On the other hand, models from G1 performed better for longer calibration periods (C3 and C4) (i.e., average NSE 0.78, average RSR 0.47) and validation periods (V3 and V4) (i.e., average NSE 0.82, average RSR 0.42), than models from G2 (i.e., for C3 and C4 average NSE 0.76 and average RSR 0.49; for V3 and V4 average NSE 0.79 and average RSR 0.45).

5. Discussion

5.1. Model analysis

The derived rainfall-runoff models can be classified as lumped (regarding spatial resolution) and continuous (regarding temporal resolution) (Fletcher et al., 2013). The proposed tool enabled a systematic comparison of three alternative infiltration methods (i.e., SCS CN, VARUK, and UKWIR), allowing also combinations of these methods. This is a unique and novel approach, as normally only one infiltration method is used within one rainfall-runoff model. The developed knowledge library, compliant with the ProBMoT tool, enabled the automatic generation and calibration of these models. Based on the criteria for assessing models' goodness of fit proposed by Moriasi et al. (2007) and presented in Table 3, the models on average had »very good« performance for the calibration periods C1, C2, and C4 and »good« performance for the calibration period C3. In the validation process, all models had »very good« performance for all validation periods, confirming the usefulness and efficiency of the proposed approach for calibration of model parameters. In general, the best performance was achieved by model M3, with an average NSE value of 0.80 for the calibration periods and an average NSE value of 0.88 for the validation periods. The second-best performance was achieved by model M2, with an average NSE value of 0.78 for the calibration periods and an average

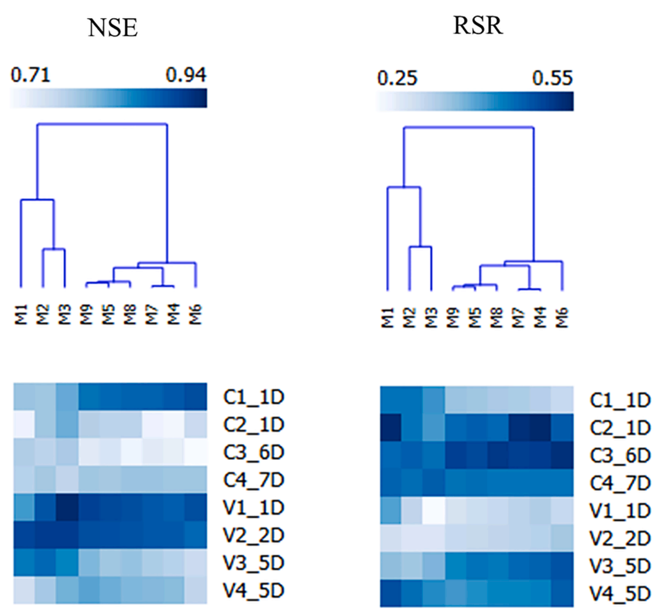

Fig. 8. The heat map resulting from hierarchical clustering of the 9 models represented by their NSE values (left) and RSR values (right) on all of the 8 periods.

NSE value of 0.87 for the validation periods. However, some of the other models performed better for individual rainfall periods or achieved similar performance. This highlights the fact that no general conclusion can be made on which model is better, since model performance results are greatly influenced by the characteristics of calibration and validation periods (e.g., rainfall intensity, number of (sub) rainfall events …). Furthermore, this was also not the intention of this research. The true value and contribution of this research is the discovery of new knowledge in the urban runoff-modelling domain by automated modelling. Namely, the best performance was achieved by models that used a combination of two different infiltration methods, in contrast to the usual approach of using a single infiltration method.

5.2. Automated approach: advantages and limitations

Urban runoff models can be either mechanistic, i.e. based on mathematical formulations of physical phenomena, or data-driven, also known as black-box models, learning from the relationship between the measured input and output data, with no description of the internal functioning of the system. Frequently, artificial neural networks are employed to develop data-driven rainfall-runoff models (Troutman et al., 2017). Compared to these types of automated modelling approaches, i.e. neural networks, our approach provides more transparency, i.e. it is an automated way for constructing mechanistic model structures. The automation is used for composing viable model structures and calibration – the two most time consuming processes in the commonly followed modelling procedure. In addition, the search through the space of models is automated, i.e. systematic and avoids human errors.

In order to build fully distributed models, hydraulic processes (i.e., pipe flow) should be included. Due to some limitations of the ProBMoT tool, only hydrological processes were included. Firstly, based on the required structure of the conceptual model, each pipe and manhole within the system would have to be presented as a separate compartment, thus significantly increasing model complexity and prolonging computation. Secondly, ProBMoT does not support the encoding of difference equations and conditional statements (e.g., if-then rules). Additionally, all the equations included in the library must use the same time resolution. Hydraulic (pipe flow) modelling is crucial when modelling complex and large sewer systems. In our case, the case study area and the adjacent sewer system were relatively small, thus the hydraulic (pipe flow) modelling would not significantly affect the outflow dynamics.

The three alternative infiltration methods (i.e., SCS CN, VARUK, and UKWIR) were selected and integrated into the knowledge library, as they were not affected by the above-mentioned limitations of the ProBMoT. On the other hand, some other frequently used infiltration methods (e.g., Horton, Green-Ampt) were not integrated due to the current ProBMoT limitations. In the future, we plan to overcome some of these ProBMoT limitations. This would allow us to upgrade the knowledge library with hydraulic processes and to include additional infiltration methods.

6. Conclusions

In this study, an automated equation (model) discovery approach was applied to the field of urban runoff modelling. First, a new library of model components, compliant with the equation discovery tool ProBMoT was developed, formalizing the knowledge on urban runoff modelling. Next, a conceptual model of the experimental urban subcatchment within the city of Ljubljana, Slovenia, was defined. The proposed methodology enabled the discovery of optimal structure and parameters' values of the rainfall-runoff models based on the pipe flow measurements, including combination of infiltration methods within a single model structure, which represents a novelty in urban hydrological research. The main findings of the study are as follows:

a) The proposed automated model discovery approach for finding the optimal rainfall-runoff models proved to be very efficient. Nine rainfall-runoff models were created that generally had »good« or »very good« performance.

b) The models performed better for validation events with a more stable/constant flow, scoring higher NSE coefficient values and lower RSR coefficient values.

c) Based on the model performance evaluation, two groups of models could be identified, based on whether the SCS CN infiltration method was assigned to the pervious area of the catchment.

d) The best performance was achieved by models that used a combination of two different infiltration methods, i.e. the SCS CN infiltration method for the pervious area in combination with one of the other two infiltration methods for the impervious area.

e) Finally, this approach is transferable to any catchment and enables the discovery of viable rainfall-runoff models, best fitted to local specific conditions on one hand, and facilitates the validation and revision of established rainfall-runoff models on the other hand.

CRediT authorship contribution statement

Matej Radinja: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Visualization. **Mateja Škerjanec:** Methodology, Software, Validation, Writing – review & editing. **Mojca Šraj:** Methodology, Validation, Writing – review & editing. **Sašo Džeroski:** Methodology, Software, Validation, Writing – review & editing. **Ljupčo Todorovski:** Methodology, Software, Validation, Writing – review & editing. **Nataša Atanasova:** Conceptualization, Methodology, Software, Validation, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 5
Discovered rainfall-runoff models with calibrated parameters.

	Units	M1		M2		M3		M4		M5		M6		M7		M8		M9	
		sub1	sub2	sub1	sub2	sub1	sub2	sub1	sub2	sub1	sub2	sub1	sub2	sub1	sub2	sub1	sub2	sub1	sub2
		SCS CN	SCS CN	UKWIR	SCS CN	VARUK	SCS CN	SCS CN	UKWIR	UKWIR	UKWIR	VARUK	UKWIR	SCS CN	VARUK	UKWIR	VARUK	VARUK	VARUK
area	m^2	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000	150,000
slope	m/m	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
width	m	5469	7500	5000	7220	5000	6619	5000	6966	5000	7500	5000	7221	5000	7500	5000	6439	5000	7500
depstordepth	m	0.00005	0.00050	0.00015	0.00052	0.00023	0.00290	0.00005	0.00072	0.00020	0.00130	0.00030	0.00176	0.00005	0.00050	0.00020	0.00141	0.00020	0.00120
n	$s/m^{1/3}$	0.08	0.18	0.08	0.15	0.08	0.15	0.08	0.15	0.08	0.15	0.08	0.15	0.08	0.15	0.08	0.18	0.08	0.15
CN		99	64	null	60	null	31	99	null	null	null	null	null	99	null	null	null	null	null
PIMPimp		100	0	100	0	100	0	100	0	100	0	100	0	100	0	100	0	100	0
IF		null	null	1.00	null	0.50	null	null	1.00	0.96	0.89	0.98	0.50	null	1.00	1.00	0.50	1.00	0.77
B		null	null	0.64	null	null	null	null	0.57	0.50	0.71	null	0.73	null	null	0.64	null	null	null
PIimp		null	null	0.55	null	null	null	null	0.00	0.13	0.73	null	0.00	null	null	0.02	null	null	null
PFimp		null	null	10.00	null	null	null	null	12.38	13.78	11.86	null	11.93	null	null	14.16	null	null	null
PIMPp	mm	100	0	100	0	100	0	100	0	100	0	100	0	100	0	100	0	100	0
NAPI	mm	null	null	0.00	null	39.55	null	null	28.58	35.11	36.69	25.68	37.95	null	14.40	0.00	12.80	36.23	13.05
PIp		null	null	0.86	null	null	null	null	0.81	0.83	0.85	null	0.83	null	null	0.88	null	null	null
Cr		null	null	0.86	null	null	null	null	0.83	0.80	0.82	null	0.88	null	null	0.96	null	null	null
SPR		null	null	0.20	null	null	null	null	0.70	0.10	0.49	null	0.48	null	null	0.10	null	null	null
PFp	mm	null	null	30.00	null	30.10	null	null	38.00	43.89	31.90	35.99	34.46	null	48.73	34.49	43.50	32.92	50.00

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Appendix A

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