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Articles

Methodology for calibration/validation of deterministic models in the catchment

Metodología para calibración/validación de modelos determinísticos en cuencas hidrográficas

Edwin Arley Toledo-Cubillos[1], ORCID: https://orcid.org/0000-0003-1391-3215

Alberto Galvis-Castaño[2], ORCID: https://orcid.org/0000-0002-4158-1919

[1]Instituto Cinara, Facultad de Ingeniería, Universidad del Valle, Cali, Colombia, edwin.toledo@correounivalle.edu.co

[2]Instituto Cinara, Facultad de Ingeniería, Universidad del Valle, Cali, Colombia, alberto.galvis@correounivalle.edu.co

Corresponding author: Edwin Arley Toledo-Cubillos, edwin.toledo@correounivalle.edu.co

Abstract

To improve the predictions of a deterministic hydrological model, it is necessary to calibrate and validate the model so that it can be used to predict the system's behavior reliably for different conditions. This article presents the implementation of a methodology for calibration/validation deterministic hydrological models. Three blocks were considered: 1) creation and generation of precipitation intensities and random parameters to be used to obtain the simulated flows, which were stored in a database administrator; 2) the parameters obtained in block 1, are grouped to obtain the interval frequencies; 3) combination of the interval frequencies of the most influential parameters, to obtain the best combination. The methodology developed was applied to three sub-basins of the Meléndez River, in Cali, Colombia. We used more than 40 rain events in each case, and we applied the Storm Water Management Model (SWMM) to simulate the flow. The Nash-Sutcliffe determination coefficients were used to evaluate the calibration/validation process. The values obtained were more significant 0.70 for three events in the three sub-basins. It was evidenced that it is possible to find a set of feasible parameters that adjust to the different events evaluated.

Keywords: Calibration-validation, deterministic modeling, SWMM model.

Resumen

Para mejorar las predicciones de un modelo hidrológico determinístico se requiere calibrar y validar el modelo de tal forma que se pueda utilizar para predecir el comportamiento del sistema de manera confiable para diferentes condiciones. Este artículo presenta la implementación de una metodología de calibración/validación de modelos hidrológicos determinísticos, considerando tres bloques: 1) creación y generación de intensidades de precipitación y parámetros aleatorios a utilizar para obtener los flujos simulados, los cuales se almacenan en un administrador de base de datos; 2) los parámetros obtenidos en el bloque inicial se agrupan para obtener las frecuencias de intervalo; 3) el bloque correspondiente a la combinación de las frecuencias de intervalo de los parámetros más influyentes para obtener la mejor combinación. La metodología desarrollada se evaluó mediante su aplicación en tres subcuencas del río Meléndez, en Cali, Colombia. Se utilizaron más de 40 eventos de lluvia en cada caso y se aplicó el modelo SWMM para simular los flujos observados. Se usaron los coeficientes de determinación de Nash-Sutcliffe para evaluar el proceso de calibración/validación. Los valores obtenidos fueron superiores a 0.70 para tres eventos en las tres subcuencas. Se evidenció que es posible encontrar un conjunto de parámetros factibles que se ajusten a los diferentes eventos evaluados.

Palabras clave: calibración-validación, modelación determinística, modelo SWMM.

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Introduction

Deterministic hydrological models contain component parameters that must be adjusted to the specific place being evaluated, comparing the observations with the results obtained from the model application. This process is defined as calibration. Later, it is necessary to include an evaluation of the confidence of the results, that is, the performance of these, what we call validation. These processes are indispensable when making decisions using this type of model.

The parameters represent the intrinsic characteristics of the system, and that the user specifies as external to the model. They can be of two

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types: those intended to reflect the specific aspects of the dynamics of a process and those intended to reflect the particular characteristics of the place where the model is being applied (Beven, 2009), the latter being the calibration parameters.

Sometimes, in theory, the values of the parameters can be determined by direct measurements made at the study site. However, some parameters are conceptual representations of the abstract catchment, and they must be determined indirectly through a calibration process (Gupta, Sorooshian, & Yapo, 1998). Calibration parameters directly determine the model's reliability, accuracy, and forecast quality (Zhang, Wang, & Meng, 2015).

In the calibration of hydrological models, some researchers have focused on finding the "perfect" calibration algorithm (Vrugt & Robinson, 2007), while other researchers have focused on the choice of the best objective function (Reichert & Schuwirth, 2012). Although they are optimization processes specializing in finding the optimal parameters, it faces a fundamental problem (Beven, 2009) considering that optimal parameter sets are not always the best or unique when using new performance measures or prediction periods. This makes the situation even more critical by trying to find a single "optimal" set of parameters that avoids considering other feasible parameter sets (Gupta *et al*., 1998). This is mainly due to the ambiguity of the parameters, known as "Equifinality" or structural errors of the model (Wagener, Wheater, &

Gupta, 2004). However, suppose some physical parameters such as area, width and slope cannot be uniquely identified. In that case, they cannot be deterministically linked to the physical characteristics of the sub-catchment (Wheater, McIntyre, & Wagener, 2008), which would imply that the models could not be used to make predictions, which is one of their main objectives. On the other hand, it is essential to consider that the values of some parameters, such as infiltration and evaporation, are not necessarily constant since they vary according to space and/or time.

Calibration is not only the search for the best set of parameters; it also corresponds to the search for the distribution of likely parameters of the model. Probabilistic estimation techniques and methods have been developed to find a joint probability distribution of the parameters. In the procedure, the estimation of the parameters is not carried out in a single point but with probabilistic descriptions of uncertainty on the domain of the parameter (Chu, Gao, & Sorooshian, 2010), using a likelihood function. We find the Generalized Likelihood Uncertainty Estimation (GLUE) methodology of Beven and Binley (1992) within these methods. GLUE is one of the most used methods in calibration and quantification of uncertainty in deterministic hydrological models due to its conceptual simplicity, ease of implementation and use, and its ability to handle different error structures and models without significant modifications to the method itself. However, the literature has questioned the method because the distributions of parameters and limits derived from GLUE are subjective and do not have a clear statistical meaning. In addition, this method is criticized for proposing a unique solution when it is expected that many sets of parameters can be equally good at predicting system behaviors (Blasone *et al*., 2008).

The difficulty in adjusting the calibration parameters for the different conditions of a sub-catchment is mainly associated with: 1) the low availability of data and the quality of these data (Kleidorfer, Möderl, Fach, & Rauch, 2009); 2) existing calibration methodologies and techniques are limited to one unit in the integration of multiple events (Dayaratne & Perera, 2004; Shinma & Reis, 2014) ; 3) the lack of efficiency in characterizing the response surface in the spatial model (Beven, 2009); 4) the use of the objective functions as a measure of model performance, to guide and accept the stoppage of searching for the parameters since it can influence the distribution of the same (magnitude and shape) (Deletic *et al*., 2012); 5) the high consumption of computational resources and time.

This paper aims to implement a calibration/validation methodology in a deterministic hydrological model at the catchment level, considering the quantity component. The methodology considers three basic principles to find calibration parameters that fit different scenarios evaluated. The first principle is using a database manager, an administrator of a set of data, which are stored and have similar characteristics. The second principle uses tables of frequency distributions to numerically describe the shape and composition of the set of data grouped across intervals. The third principle is the combination of the ranges to find datasets in an unspecified order. The methodology was evaluated in three sub-catchments of the Meléndez River, located in Cali, Colombia. The deterministic hydrological Storm Water Management Model (SWMM) was used to obtain the hydrographs used as "observed" flows. After creating some hypothetical parameters and the use of more than 40 rainfall records obtained from the study area.

Methodology

The development of the calibration/validation methodology in deterministic hydrological models, was based on three blocks that make up the three principles of the methodology (see Figure 1).

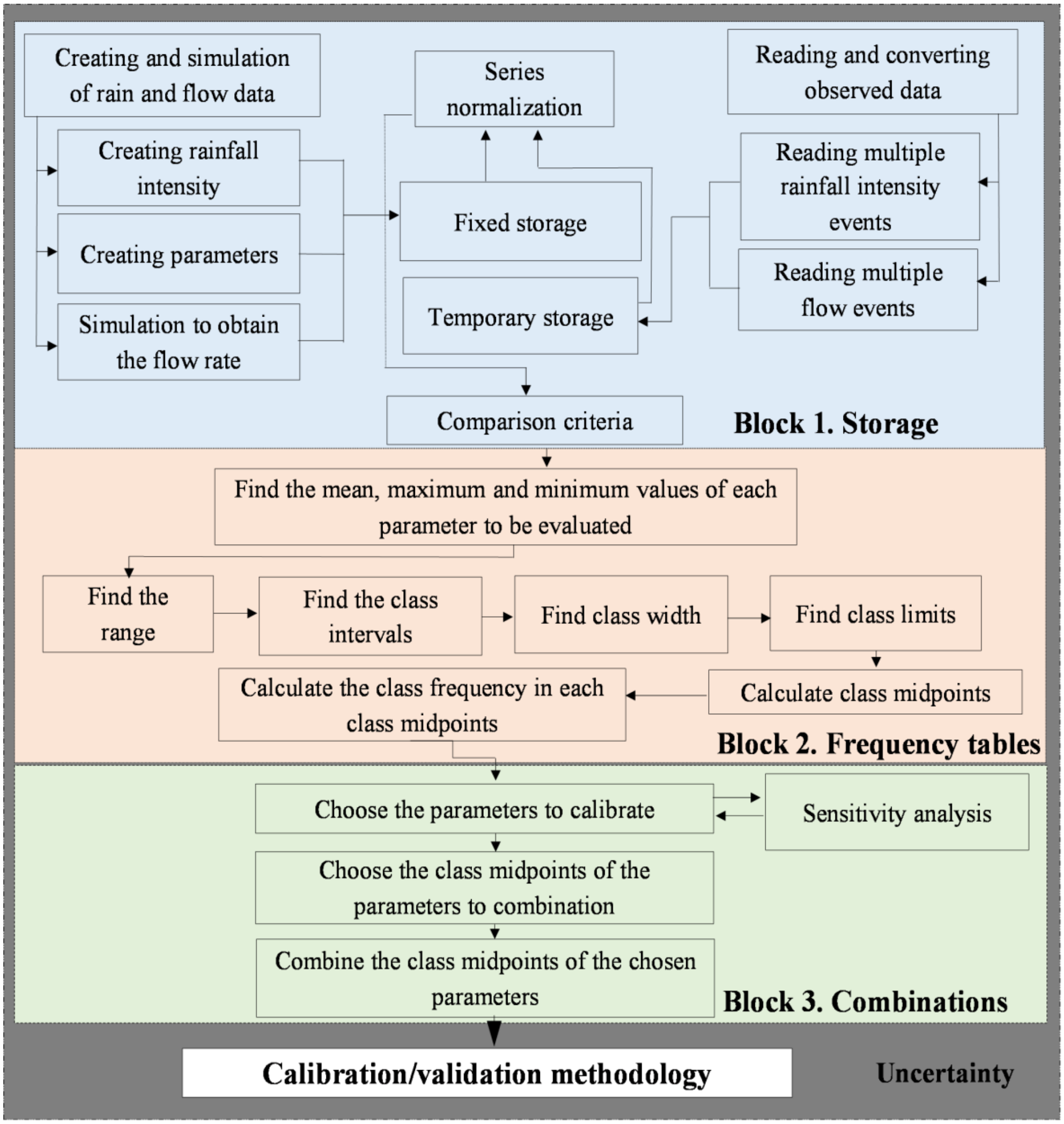

Figure 1. A general outline of calibration/validation methodology.

First block. Standardized series and storage

The first block used a database manager such as MariaDB and a deterministic hydrological model such as Storm Water Management Model (SWMM). The model was used to obtain the flow rates after simulating thousands of precipitation intensity events and calibration parameters that were randomly created. The information obtained and entered into the model is stored. This information includes the series of precipitation intensity, parameters, and hydrographs.

The database manager helped map and characterize the model's entire response surface in a sub-basin, allowing to store all the information of the respective runs made to the model. Later, this information was associated with the observed flow series values. The database manager also helped to make searching for the respective series efficient and optimal.

It should be noted that this process applies only to deterministic models since it represents a "reality" in a simplified form, expressed mathematically, where it seeks to simulate the real conditions through the cause-effect relationships. In this case, the hydrographs corresponding to the effects and the parameters would correspond to the causes.

The first step was to create and delimit the parameters with maximum and minimum values that they can take in a sub-catchment, taking into account real physical values presented in the study area. This step requires prior knowledge of the study area.

Table 1 presents the calibration parameters and the minimum and maximum values that can be taken for the sub-catchments of the Meléndez River. The values were obtained from prior knowledge of the study area and expertise with similar morphological characteristics in the catchment. Additionally, it had the support of bibliographical references. Table 1 also presents the equations used for the random creation of calibration parameters, where σ is a random value between 0 and 1.

Table 1. Minimum and maximum values are considered for the calibration parameters of the SWMM model in the three sub-catchments of the Meléndez River, Cali, Colombia.

Sub-catchment parameters	Minimum Value	Maximum Value	Units	Equation
Width of the sub-catchment (*Aw*)	0	1 549	m	$Aw = \text{Area}/La$ (1)

Slope of the sub-catchment (*Slope*)	0	100	%	$Slope=\sigma*100$ (2)
Percent of impervious area of the sub-catchment *(% Imperv*)	0	100	%	$\%Imperv=\sigma*100$ (3)
Impervious area roughness (*N-imper*)[a]	0.01	0.02	---	$N\text{-}Imper=(\sigma*0.01)+0.01$ (4)
Pervious area roughness (*N-Perv*)[a]	0.021	0.8	---	$N\text{-}Perv=(\sigma*0.779)+0.021$ (5)
Depth of depression storage on the impervious portion of the sub-catchment (*S-Imperv*)[b]	0	50	mm	$S\text{-}Imperv=\sigma*50$ (6)
Depth of depression storage on the previous portion of the sub-catchment (*S-Perv*)[b]	0	150	mm	$S\text{-}Perv=\sigma*150$ (7)
Percent of the impervious area with no depression storage. (*PctZero*)	0	100	%	$PctZero=\sigma*100$ (8)
Minimum infiltration rate on the Horton curve (*MinRate*)[c]	0	200	mm/h	$MinRate=\sigma*200$ (9)
Maximum infiltration rate on the Horton curve (*MaxRate*)[C]	10	450	mm/h	$\mathrm{MaxRate}=(\sigma*440)+10$ (10)

Infiltration rate decay constant for the Horton curve (*Decay*)[c]	0	32	1/h	$Decay = \sigma * 32$ (11)

Reference: a) (Crawford & Linsley, 1966); b) (Gómez, 2007); c) ((Pitt, Lantrip, Harrison, Henry, & Xue, 1999; Rossman, 2005).

The SWMM model represents the sub-catchment as a rectangle, where the area is equal to the product of length by width (Rossman, 2005). In Equation (1), Aw is the width, and La is the length. For this study case, the maximum width that a sub-catchment can reach is 1 549 meters, which corresponds to the square root of 2 400 000 m2 (240 ha) of area, which is the maximum value allocated for a sub-catchment.

The process continued with creating the precipitation intensity series; to do this, the number of data that makes up a series of intensity was delimited. In this research, a range between 6 and 25 registers was used. According to their respective temporal distribution, it was necessary to determine the respective maximum values that each data could reach. That is, each value that makes up the intensity series can be a maximum intensity data, as presented in Equation (12), where σ is a random value between 0 and 1 and *intmax* is the maximum intensity for each time interval, which is given by the modeler, according to the historical records from the weather stations for which information was obtained. Historical maximum values of 50 mm/h (CVC, 2015) were found in the sub-catchment of the Meléndez River for 10-minute intervals:

$$Intensidad=(\sigma*Intmax) \tag{12}$$

Creating a set of calibration parameters and a series of intensities allowed obtaining the simulated flow rates in the SWMM model. All of the above were permanently stored in the database manager, where they (flows and intensities) were converted into standard series (Figure 1). Each value of a series of precipitation intensity and the respective values of its hydrograph obtained from the model were divided by the most significant number found in their series. It would get different groups of decimal numbers and an integer between 0 and 1. To this process, we define standard codes or series normalization. The normalization was carried out to facilitate the search for the flow rate in the database since the shape of a hydrograph can represent it with numbers at the same scale, i.e., normalized. The standardized series of intensity and flow rates were also permanently stored in the database manager.

The MariaDB database manager obtained five permanently stored series: the precipitation intensity, simulated flow rates, sets of parameters, and the respective standardized series of both intensity and simulated flows. The set of the five stored series was called "a run," which was identified with a unique number in the database manager. The objective of when the respective flow comparisons were made would be possible to determine which parameters are associated with this hydrograph. For the sub-catchment studied, 60000 runs were used, i.e., 60 000 randomly created sets and series of parameters calibrated and rainfall intensities, respectively; 60 000 flow rates series obtained in the SWMM model and 60000 standardized series for both intensities and flow rates.

The normalization process was repeated for the observed series of both intensity and flow rates, but with the difference that they were stored temporarily and externally in the database. In this work, we used the computer's random-access memory or RAM.

Considering that the "observed" series of flows corresponded to the hydrographs obtained in the SWMM model, we had information on the area for the three sub-catchments studied after entering more than 40 events of precipitation intensity series.

The next step was finding the series of the standardized hydrographs, simulated, and stored in the database manager, which resemble the standard series of the observed hydrographs. For this purpose, two search criteria were used.

The first criterion was to assign a percentage of the error to the standard series of the simulated hydrographs stored in the database manager related to all the standard series of the observed hydrographs. A normalized series of a simulated and permanently stored hydrograph is made up of data (6 to 25 data for the present study); each data should not be less than or higher than the percentage of search error.

The second criterion allowed several errors in the data that make up the series of hydrographs simulated and stored in the database about the first criterion. The normalized series of a hydrograph stored in the database can have data beyond the assigned search range in the first criterion, so an error rate was allowed in the data that make up the stored hydrographs for this study were used: for the first criterion, an error rate of 10%, while for the second criterion the number of errors that are allowed corresponded to 2.

Second block. Application of frequency distributions

In the second block, tables or frequency distributions were applied to the set of calibration parameters, which formed the standard series of the simulated hydrographs stored in the database manager. These series passed the search criteria in block 1 after comparing both simulated and observed standardized hydrographs.

After obtaining the results from block 1, each calibration parameter will contain different values according to the solutions obtained from the database for all the evaluated events. This would imply a parametric uncertainty associated with not finding a unique value that fits all the events being assessed. However, finding different deals for a specific parameter that can be grouped into a single value with a repetition frequency results in validation.

The use of the frequency distribution tables in the sets of calibration parameters was carried out to the group, condense and synthesize in a more compacted way all the values of the calibration parameters obtained in block 1. The steps were as follows: 1) the set of calibration parameters obtained from the database after comparison was organized to find the mean, maximum and minimum values in each parameter, 2) the range was found, 3) the number of class intervals were defined, 4) the width of the class was found, 5) lower and upper-class limits were defined, 6) the class midpoints were calculated and 7) the class frequency was calculated.

Third block. Combination of the class midpoints of the most influential parameters

The class midpoints of the calibration parameters obtained in block 2 were combined and evaluated in the third block. But it is advisable to combine and evaluate only the most sensitive parameters, which represent a higher rate of change in the flow rates when varying them. The calibration/validation process is more efficient in terms of computational resources. The remaining parameters, which are not combined or evaluated, were obtained from a mean of the frequency table or the modeler's knowledge.

The number of combinations of the class midpoints of the parameters to be calibrated can be described mathematically according to Equation (13):

$$C = F^{P} \tag{13}$$

Where:

C= number of combinations

F= number of class midpoints to evaluate in each parameter

P= parameters to be calibrated

Equation (13) is used as long as the system under study has the same class midpoints options in the evaluation parameters; otherwise, the following equation is used:

$$C= \prod_{K=1}^{n} F_k \tag{14}$$

Where:

F_k= parameter possibilities to calibrate

With the combinations obtained from the class midpoints of the parameters to be calibrated, we evaluated them one by one for four random events in each sub-catchment. The evaluation was carried out to analyze which parameters best suited the observed flows. An objective function was used as a measure of comparison. The objective function used corresponded to the Nash-Sutcliffe coefficient of determination (Nash & Sutcliffe, 1970), which measures how much of the variability of the observations is explained by the simulation, where values close to one represent a better fit.

The steps for the development of block 3 were as follows: 1) The most sensitive parameters were chosen for the SWMM model, which according to authors such as Rossman and Huber (2015), correspond to depression storage in impervious areas, percent of the land area which is impervious, percent of the impervious area with no depression storage, width and slope; 2) the class midpoints of the most sensitive parameters that were combined were chosen, which could correspond to the highest frequency number; 3) the different class midpoints of the parameters chosen in step 1 were combined; 4) for parameters that were not chosen as sensitive or influential, values were taken as an mean or like a default value depending on the experience or knowledge of the area.

The three blocks are within a framework of uncertainty (see Figure 1). It is always present in any modeling process and originates from various sources, from model formulation to data collection used for calibration and validation (Deletic *et al*., 2012).

Implementation of the new methodology

To evaluate the calibration/validation methodology developed, three sub-catchments of the Meléndez River located in Cali, Colombia, were taken (Figure 2). Sub-catchments 2 and 3 correspond to rural areas whit slopes between 15 and 5 0%, some population settlements, and some small-scale agricultural activity. Sub-catchment 1 is urban and comprises slopes between 5 and 15 % (Univalle & Dagma, 2004).

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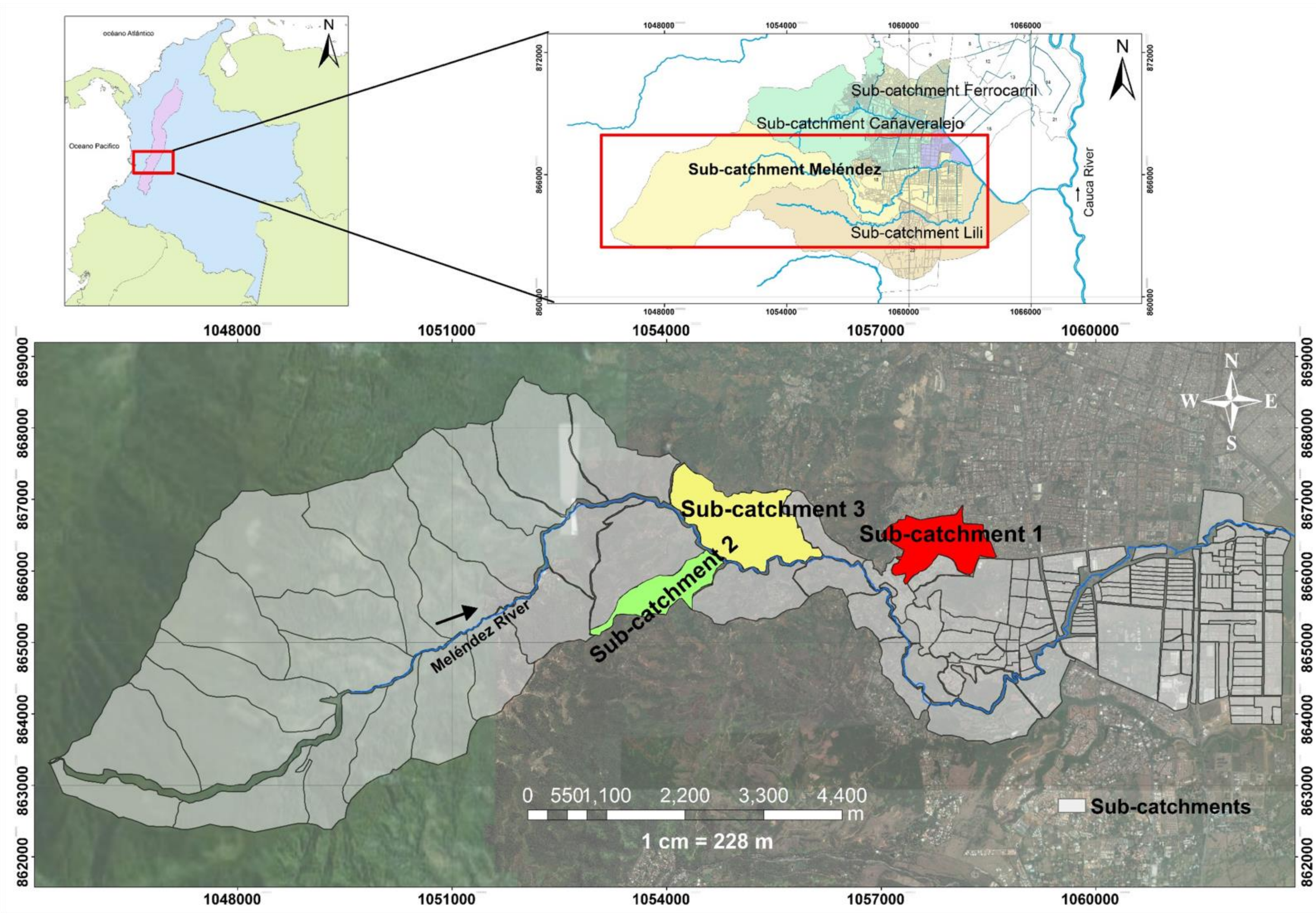

Figure 2. Location of the 3 study sub-catchments on the Meléndez River, Cali, Colombia.

For this study case, some hypothetical parameters were created in the SWMM 5.1 model (see Table 2), except for the area, slope, and width that had the respective location information. To obtain the respective hydrographs, 45 series of observed rainfall intensity (CVC, 2015) were used for sub-catchment 1, and 50 series of observed rainfall intensity (CVC, 2015) were used for sub-catchment 2 3, respectively. This is how 45 series of simulated flows were obtained in sub-catchment 1 and 50 for sub-catchment 2 and 3, corresponding to the "observed flows" for this study case.

Table 2. Initial values of the calibration parameters of the SWMM model for the Meléndez river sub-catchments were considered in the study case.

Parameters	**Sub-catchment 1**	**Sub-catchment 2**	**Sub-catchment 3**
Area -*ha*	90.2	60	180
Width- *m*	1 315	600	1 400
Slope- *%*	15	35.5	50
percent of impervious (*% Imperv*) *	80	40	35
Impervious area roughness (*N-imper)**	0.016	0.015	0.018
Pervious area roughness (*N-Perv*) *	0.25	0.4	0.5
Impervious area depression storage (*S-Imperv*)- *mm**	10	6	15

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Pervious area depression storage (*S-Perv*)- *mm**	20	30	35
Percent of the impervious area with no depression storage (*PctZero*)- *%**	25	5	12
Maximum infiltration rate on the Horton curve (*MaxRate*)- *mm/h**	80	150	200
Minimum infiltration rate on the Horton curve (*MinRate*)- *mm/h**	50	70	80
Infiltration rate decay constant for the Horton curve (*Decay*)- *1/h**	7	7	10

* Parameters created hypothetically in sub-catchment.

Results

The first block, specifically after the two filters (criteria 1 and 2), was found in the database: 34, 69, and 19 hydrographs standardized for sub-catchment 1, 2, and 3, respectively, where each normalized hydrograph is associated with a set of calibration parameters.

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As shown in Table 3, the arithmetic mean, the maximum and minimum, the range, the class intervals, and the class's width for each calibration parameter were calculated for the second block. Later, as shown in Table 4, the frequency table was created, where four parameters of the five chosen to be combined are presented.

Table 3. Results of indicators of the calibration parameters for the sub-catchments of the Meléndez River.

Indicator	Width (m)	Slope (%)	% Imperv (%)	N-imperv	N_Perv	S-Imperv (mm)	S-Perv (mm)	PctZero (%)	MaxRate (mm/h)	MinRate (mm/h)	Decay (1/h)
Sub-catchment 1											
Mean	814.3	9.40	66.4	0.015	0.46	25	75.3	51.2	194.3	78.5	16.66
Maximum	1 528.2	40.41	99.9	0.020	0.78	48.7	150	97	447.1	195.7	31.52
Minimum	81	0.15	6.3	0.010	0.07	1.3	2.6	5.7	21.5	3.7	0.08
Range	1 447.2	40.26	93.6	0.010	0.70	47.4	147.4	91.3	425.6	192.0	31.45
Class intervals	6	6	6	6	6	6	6	6	6	6	6
Class width	241.2	6.71	15.6	0.002	0.12	7.9	24.6	15.2	70.9	32.0	5.24
Sub-catchment 2											
Mean	861.4	33.275	69.2	0.016	0.41	24	68.8	49.87	202.6	74.3	15.47
Maximum	1 584.7	98.713	99.9	0.020	0.8	49.8	147.4	97.90	435.4	186.4	30.85
Minimum	107	0.006	5.4	0.010	0.02	0.8	1	0.14	13.7	4.8	0.72
Range	1 477.7	98.704	94.5	0.009	0.77	49.1	146.4	97.76	421.6	181.7	30.13
Class intervals	7	7	7	7	7	7	7	7	7	7	7
Class width	211.1	14.101	13.5	0.001	0.11	7	20.9	13.97	60.2	26.0	4.30
Sub-catchment 3											
Mean	799	44.9	73.1	0.016	0.37	16.7	74.97	46.26	259.6	90.9	17.9
Maximum	1 543	90.5	99.2	0.019	0.77	40.7	142.88	85.28	444.8	192.6	32.0

Minimum	113	6	36.7	0.011	0.02	1.1	0.52	0.10	20.4	0.9	1.1
Range	1 430	84.5	62.6	0.008	0.74	39.6	142.36	85.18	424.4	191.7	30.9
Class intervals	5	5	5	5	5	5	5	5	5	5.0	5
Class width	286	16.9	12.5	0.002	0.15	7.9	28.47	17.04	84.9	38.3	6.2

Table 4. Results of the frequencies of the parameters to be calibrated in the sub-catchments of the Meléndez River.

N° registration	**Lower Class**	**Lower Class**	**Lower Class**	**Frequency**	**N° registration**	**Lower Class**	**Lower Class**	**Lower Class**	**Frequency**
Sub-catchment 1									
Frequency of the width					*Frequency of the percent of impervious*				
1	81	322.2	201.6	4	1	6.3	21.9	14.1	3
2	322.2	563.4	442.8	6	2	21.9	37.5	29.7	3
3	563.4	804.6	684	8	3	37.5	53.1	45.3	3
4	804.6	1 045.8	925.2	6	4	53.1	68.7	60.9	7
5	1 045.8	1 287	1 166.4	4	5	68.7	84.3	76.5	7
6	1 287	1 528.2	1 407.6	6	6	84.3	99.9	92.1	11
Frequency of the slope					**Storage depth frequency for impervious zones**				
1	0.15	6.86	3.51	19	10	1.3	9.2	5.3	10
2	6.86	13.57	10.22	6	1	9.2	17.1	13.2	1
3	13.57	20.28	16.93	6	6	17.1	25.0	21.1	6
4	20.28	26.99	23.64	2	3	25.0	32.9	29.0	3
5	26.99	33.70	30.35	--	6	32.9	40.8	36.9	6
6	33.70	40.41	37.05	1	8	40.8	48.7	44.8	8
Sub-catchment 2									
Frequency of the width					**Frequency of the percent of impervious**				

1	107	318.1	212.6	13	1	5.4	18.9	12.2	3
2	318.1	529.2	423.7	8	2	18.9	32.4	25.7	2
3	529.2	740.3	634.8	8	3	32.4	45.9	39.2	6
4	740.3	951.4	845.8	7	4	45.9	59.4	52.7	10
5	951.4	1 162.5	1 057	11	5	59.4	72.9	66.2	14
6	1 162.5	1 373.6	1 268.1	12	6	72.9	86.4	79.7	15
7	1 373.6	1 584.7	1 479.2	10	7	86.4	99.9	93.2	19
Frequency of the slope					**Storage depth frequency for impervious zones**				
1	0.006	14.107	7.054	20	1	0.8	7.8	4.3	13
2	14.107	28.208	21.158	13	2	7.8	14.8	11.3	11
3	28.208	42.309	35.259	14	3	14.8	21.8	18.3	7
4	42.309	56.41	49.36	6	4	21.8	28.8	25.3	10
5	56.41	70.511	63.461	10	5	28.8	35.8	32.3	12
6	70.511	84.612	77.562	2	6	35.8	42.8	39.3	4
7	84.612	98.713	91.663	4	7	42.8	49.8	46.3	12
Sub-catchment 3									
Frequency of the width					**Frequency of the percent of impervious**				
1	113	399	256	7	1	36.7	49.2	43.0	3
2	399	685	542	2	2	49.2	61.7	55.5	2
3	685	971	828	3	3	61.7	74.2	68.0	5
4	971	1 257	1 114	--	4	74.2	86.7	80.5	1
5	1 257	1 543	1 400	7	5	86.7	99.2	93.0	8
Frequency of the slope					**Storage depth frequency for impervious zones**				
1	6	22.9	14.5	6	1	1.1	9.1	5.1	8
2	22.9	39.8	31.4	1	2	9.1	17.0	13.0	3
3	39.8	56.7	48.3	4	3	17.0	24.9	20.9	3
4	56.7	73.6	65.2	6	4	24.9	32.8	28.9	1

5	73.6	90.5	82.1	2	5	32.8	40.7	36.8	4

For the third block, which consisted of combining the class midpoints of the most influential parameters, we obtained: 6 480 combinations for Sub-catchment 1(slope has 5 class midpoints; apply Equation 14); 3 125 varieties for Sub-catchment 2 (the first five frequencies that were most repeated in each parameter evaluated; use Equation 13), and 2 500 combinations (width with 4 class midpoints; apply Equation 14) for Sub-catchment 3. All the results obtained from the combinations (simulated flow series) in each sub-catchment were evaluated with the Nash-Sutcliffe coefficient of determination to find the best combination of values corresponding to the parameters to be calibrated. The values of the parameters chosen to be combined are presented in Table 5 for the four events used, with their respective Nash-Sutcliffe coefficient of determination (NSE).

Table 5. Results of the calibration parameters based on combinations and Nash-Sutcliffe coefficients were obtained for the four events evaluated in the three sub-catchments of the Meléndez River.

N° combinations	Width (m)	Slope (%)	% Imperv (%)	S-Imperv (mm)	PctZero (%)	NSE 1	NSE 2	NSE 3	NSE 4

Sub-catchment 1									
4	1 166.4	10.22	76.5	13.2	28.5	0.79	0.98	0.86	0.99
12	1 166.2	16.93	76.5	13.2	28.5	0.75	0.98	0.88	0.99
20	1 407.6	10.22	76.5	13.2	28.5	0.76	0.98	0.88	0.99
Sub-catchment 2									
1	423.7	35.26	39.2	4.3	7.1	0.89	0.98	0.87	0.70
9	423.7	49.36	39.2	4.3	7.1	0.87	0.99	0.85	0.69
17	634.8	35.26	39.2	4.3	7.1	0.85	0.98	0.83	0.67
Sub-catchment 3									
8	828	65.2	43	13	8.6	0.5	0.95	0.66	0.93
16	828	48.3	43	13	8.6	0.58	0.94	0.64	0.90
32	1 400	48.3	43	13	8.6	0.43	0.97	0.70	0.97

For sub-catchment one, the NSE 1, 2, 3, and 4 are very similar for the three combinations. There are minor variations for events 1 (see Figure 3) and 3 due to the width and slope parameters which are different for combinations 20 and 12, respectively.

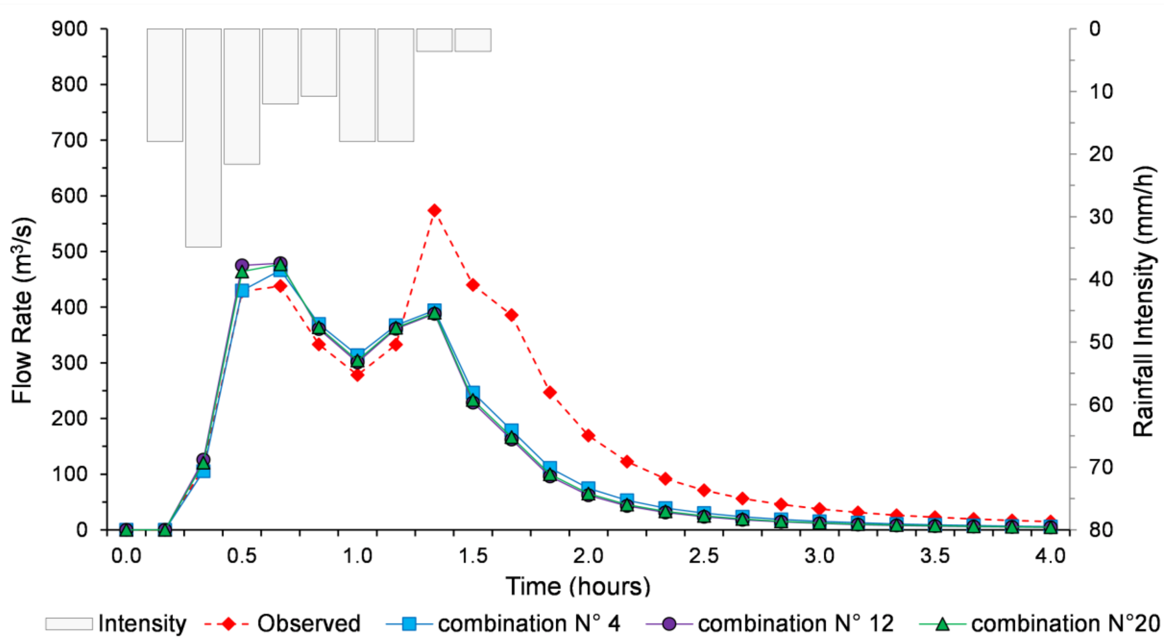

Figure 3. Rainfall intensity and observed flow rate vs. simulated flow combinations for Sub-catchment 1 in Event 1.

There is more significant variability in the NSE evaluated for sub-catchment two, both for event one and event 3 (see Figure 4). However, it is not substantial (less than five-hundredths), considering that three values of its parameters are equal (% Imperv, S-Imperv, and PctZero).

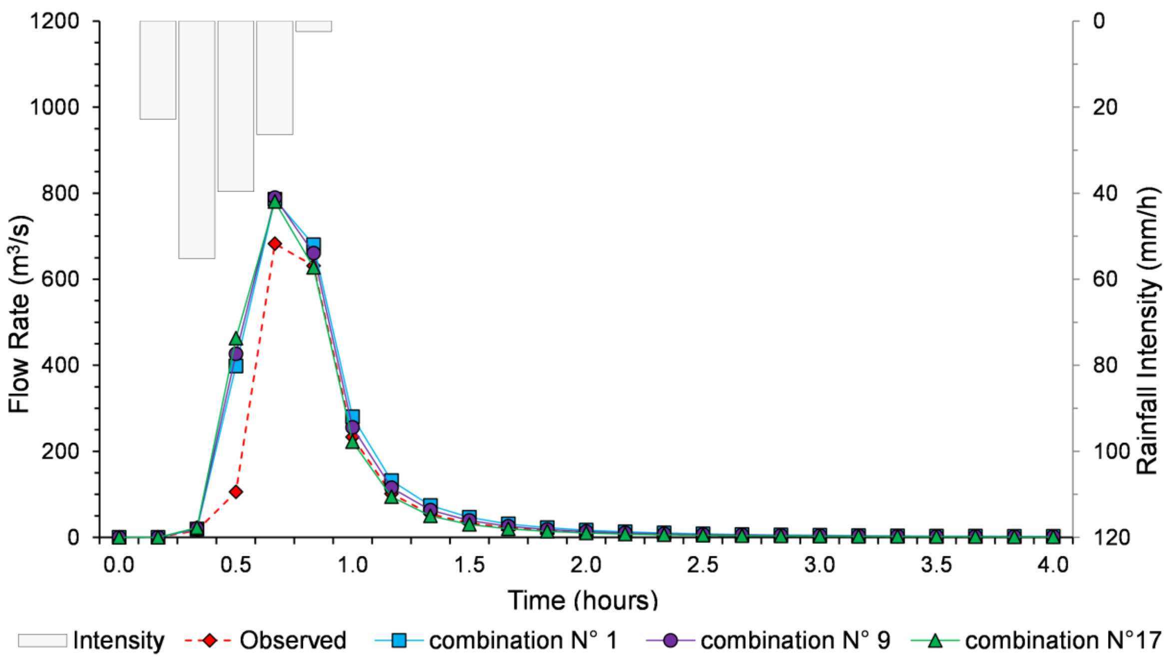

Figure 4. Rainfall intensity and observed flow *vs*. simulated flow combinations for Sub-catchment 2 in Event 3.

For sub-catchment 3, it occurs the same as Sub-catchment 2. Still, this time NSE 1 has a more significant variability concerning the other NSE evaluated (Figure 5), being the one with the lowest NSE in all events. This implies that there are some parameters that best fit specific events. However, it's essential to keep in mind that some parameters were hypothetically created, which means a unique and optimal set of parameters for the present study.

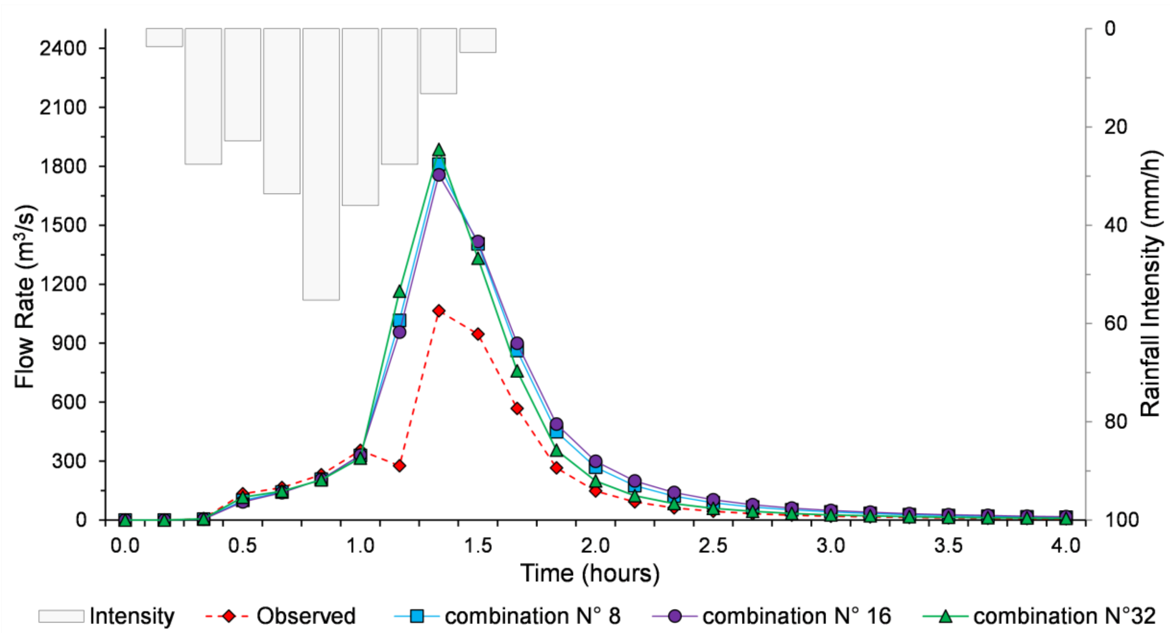

Figure 5. Rainfall intensity and observed flow *vs*. simulated flow combinations for Sub-catchment 3 in Event 1.

By having a unique set of parameters, it is established that they would apply to any event, as presented in the case study, but the sub-basins are dynamic in time and space. Therefore, it is impossible to find a single set of unique parameters that apply to all events.

Discussion

In sub-catchment 3, for combination 32, an NSE of 0.97 is obtained for event 2 (see Table 5), being an almost perfect fit (NSE=1). However, the result is deficient for that exact combination and another event (event 1) (Table 5), with an NSE of 0.43. This shows that optimal parameter sets are not always optimal when using new performance measures or prediction periods, as Beven (2009) argues.

It was evident in the results obtained that the five calibration parameters chosen to be combined corresponded to the most influential or sensitive of the SWMM model version 5.1, as argued by Kenneth, Janet, and Michael (2008). They indicate that impervious area depression storage (S-Imperv), percent of impervious (% Imperv), and percent of impervious area with no depression storage (PctZero), have a greater affectation on the hydrograph resulting from the application of the model.

Another point to note is that a single event cannot be used to calibrate or validate, as shown by the results in sub-catchments 1 and 3, specifically for events 1 and 4 (see Table 5). The calibration/validation process requires multiple events (Mourad, Bertrand-Krajewski, & Chebbo, 2005). The success of calibration and validation depends on the quantity and quality of the data (Sorooshian, Gupta, & Fulton, 1983).

Conclusions

With the calibration and validation methodology developed, it was evidenced that a set of feasible parameters can be found for different events evaluated, which can be used to make predictions in the study area but taking into account that the parameters found are not optimal and are not unique in all events.

The results of the methodology developed depended on two factors. The first factor corresponded to the form of generation storing the information (rainfall intensities, simulated flows, and calibration parameters) in the database manager. The second factor was the quantity and quality of the observed events used for the evaluation and comparison process.

Only five calibration parameters were considered in the study case, of 11 that the SWMM model must calibrate the sub-catchment. In this condition, Nash-Sutcliffe determination coefficients above 0.7 were obtained. So, it was not necessary to calibrate all the parameters as a whole, saving computational resources and time.

Overall, for the three studied sub-catchment of the Meléndez River in Cali, Colombia, the Nash-Sutcliffe determination coefficients were above 0.7, which is satisfactory. Consequently, the set of parameters obtained in each sub-catchment could be used to make decisions.

It is essential to evaluate the calibration/validation methodology developed in a instrumentalized sub-catchment, where reliable information is available on rainfall intensity and observed flows, to consider the different sources of uncertainty.

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