Madrazo-Uribeetxebarria, E.; Garmendia Antín, M.; Almandoz Berrondo, J.; Andrés-Doménech, I. (2021). Sensitivity analysis of permeable pavement hydrological modelling in the Storm Water Management Model. Journal of Hydrology. 600:1-10. https://doi.org/10.1016/j.jhydrol.2021.126525

Sensitivity analysis of permeable pavement hydrological modelling in the Storm Water Management Model

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Abstract

The Storm Water Management Model (SWMM), widely used by engineers to design or analyse stormwater networks, allows to model the so-called Low Impact Development (LID) controls, which reduce the flow conveyed to traditional networks. But, values for LID control parameters are often unknown. Furthermore, it is not always easy to link the cross-section materials to those provided by the model, particularly in the soil layer. This article provides a global sensitivity analysis for the PP type of LID control, in order to support practitioners in calibration tasks. The analysis explores what factors are the most influential and which can be fixed while calibrating a model. In particular, flow volume and peak are studied but the analysis also explores the influence of storm length and drain layer, which is optional. At the end, the most influential parameters, and those that can be neglected are presented, showing that we can focus on quite less parameters than initially given when calibrating a PP model in SWMM.

Keywords: permeable pavement,, SWMM,, low impact development,,

SUDS, sensitivity analysis, calibration,

1. Introduction

Sustainability issues are gaining increasing attention from society (Biswas, 2020), and authorities are encouraged to consider environmental dimensions of their practices, stormwater projects being no exception (Geyler et al., 2019). In that context, Sustainable Urban Drainage Systems (SUDS) or Low Impact Development controls (LID controls) are techniques that provide an improved rainwater management at source, in order to get the hydrological behaviour of urbanised land closer to predeveloped situation.

Permeable pavement (PP) is one type of such LID technique, characterised by generating a porous but, at the same time, accessible surface for pedestrians and vehicles. PPs consist of several porous layers laid over the natural soil, with a cover layer of pavement at the top allowing water to flow through. The layers are usually referred to, from the top-down: pavement, bedding, base, subbase and subgrade (natural soil) layers. The section may also include one or more geotextile layers and one or multiple drains. In any case, there is no unique layout or cross-section, as solutions adopted by practitioners are usually multiple, depending on the structural and hydrological requirements of a given application (Rodríguez-Rojas et al., 2020; Kuruppu et al., 2019; Woods Ballard et al., 2015; Mullaney and Lucke, 2014; Scholz and Grabowiecki, 2007), but also adapted to local materials and conditions.

For stormwater designing purposes or to forecast the response of a given network facing predicted weather events, it is common for practitioners to rely on mathematical models. There are several available models for the analysis of the PPs, widely detailed in Kaykhosravi et al. (2018), but few allow for an integrated hydrological-hydraulic modelling of LIDs incorporated within catchments, being Storm Water Management Model (SWMM) one of them. Hence, SWMM is a powerful instrument to carry out different studies related to various types of LID (Andres-Domenech et al., 2018), including PP. Several studies use SWMM for analysing LIDs effects on urban flooding (Qin et al., 2013), hydrologic response of an urban catchment under different scenarios (Palla and Gnecco, 2015), or prioritising sites and types for LID practices (Liao et al., 2018; Song and Chung, 2017). Besides SWMM being recommended for preliminary and detailed design objectives, it is also one of the most popular models among scientists (Kaykhosravi et al., 2018).

Similarly to other types of LID present in SWMM, PPs are defined by overlapping several layers: surface, pavement, soil, storage and drain. Figure 1.a illustrates the layer layout but, in order to run the model, it is necessary to fix the parameters defined in each of the layers (see Table 1). It is then, when allocating values to the parameters provided by SWMM, that doubts arise about which may be those that fit better to the real pavement characteristics. This is due to the lack of information on the physical properties of the materials used or, alternatively, because the layout (see Figures 1.b, .c and .d as an example) do not match predefined layers in the SWMM LID model.

With such difficulties, it is of great value knowing in advance which are the most influential parameters during model calibration. In essence, while setting up and using numerical simulation models, Sensitivity Analysis (SA) methods are invaluable tools (Iooss and Lemaître, 2015). In hydrological

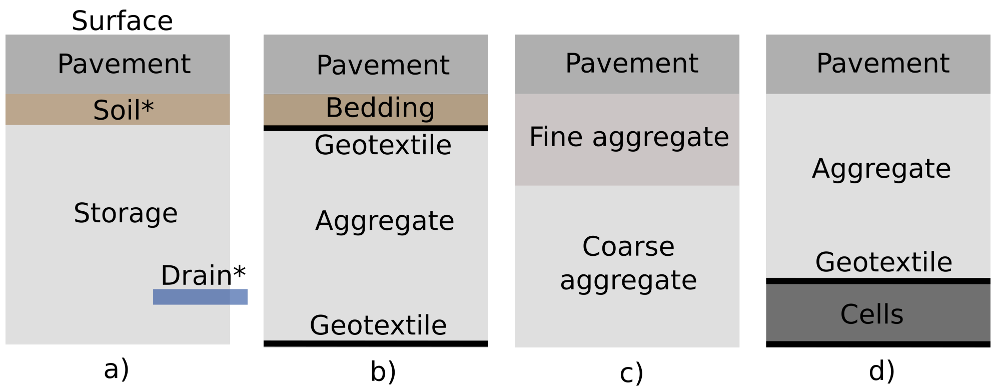

Figure 1: PP cross-sections (a) as defined in the SWMM model (b) with bedding layer and geotextiles, (c) various aggregate types, and (d) cells below aggregate with geotextiles.

modelling, the most frequent reason for conducting SA is to select the most sensitive parameters to vary during model calibration (Gupta and Razavi, 2018). Global approaches are required to perform a valid SA when models feature nonlinearities and interactions (Saltelli et al., 2019), although there are three main obstacles to perform such analysis: the computation time, the number of inputs, and the size of the input space (Pujol, 2009).

Various SA have recently been carried out on PPs based on HYDRUS model (Costa et al., 2020; Brunetti et al., 2018; Turco et al., 2017; Brunetti et al., 2016), but the analysed parameters or inputs differ from those used in SWMM. Also, several SA have been carried out previously in SWMM, a detailed list can be found in Niazi et al. (2017), but few have carried out such an analysis focusing just on LID controls and its parameters (Panos et al., 2020; Xu et al., 2019; Leimgruber et al., 2018; Peng and Stovin, 2017; Krebs et al., 2016), and most of them did it as a previous step before calibrating a certain model. Randall et al. (2020) are the only ones that explored the

PP, but they did not use a global SA, as they explored parameter variability for three cross-sections used in their study. In addition, they focused on the underdrain flow exclusively.

Besides, PPs have two particular characteristics that differentiate them from other types of LID controls (Rossman, 2015): the pavement layer is used exclusively in this type of LID control and, moreover, it is the only one where the soil layer is optional. Thus, the analysis of PP LID type would be of great value, since none of the previous studies provided a general vision for PPs in SWMM, not just valid for a particular case, but as a universal instrument for all real cases that may emerge when calibrating PPs in SWMM. If that data may be available, it could potentially be used directly by practitioners to improve the quality and efficiency of their SWMM modelling.

Therefore, the aim of this study is to investigate the influence of multiple factors on the hydrological response of PPs in both short- and long-term modelling scenarios by using the rainfall-runoff model SWMM. The problem is addressed in the following way. First, minimum and maximum values were set for explored parameters. Then, considered cases are defined, in terms of analysis length, optional layers and analysed outputs. Finally, sensitivity indices and their confidence intervals are calculated for each case. Consequently, the objectives set for the study are: (a) to check if there are differences between parameter sensitivities for the several cases studied, (b) to identify negligible and most influential parameters, and (c) to compare those parameters with the ones identified on previous SA studies.

2. Methodology

This section describes the methodology used in the three fundamental steps followed: (1) characterise the variance based SA, (2) characterise the LID model defined in SWMM, and (3) define the terms in which SA is performed.

2.1. Variance based sensitivity analysis

The Sobol method is a variance based sensitivity method (Sobol', 1990), which decomposes the model output variance into relative contributions from individual parameters and parameter interactions, as shown in equation (1). As a result, the sensitivity of a given parameter is quantified by the ratio of its contribution to the output variance, which ranges from 0 to 1 (Shin et al., 2013). The first term of the equation indicates the addition of the variance for each factor i, named $V_i(Y)$, being these variances exclusive to that factor. The second term indicates the variance due to combinations of two factors i and j, named $V_{ij}(Y)$, and so on.

$$V(Y) = \sum_{i=1}^{k} V_i(Y) + \sum_{i<j}^{k} V_{ij}(Y) + \ldots V_{12\ldots k}(Y) \tag{1}$$

Those $V_i(Y)$ terms constitute the *main effect* or the variance of the average output when the input factor X_i is fixed. The second one, constitutes the *second order effect* or the variance of the average output when the input factors X_i and X_j are fixed. Thus, if we consider how much of the total variance is due to main effect, we can define the *first-order index* given in equation (2), which represents the main effect contribution of each input factor to the variance of the output (Saltelli et al., 2008). Higher-ranking indices may be defined in the same way, such as *second-order indices* or S_{ij}.

$$S_i = \frac{V_i(Y)}{V(Y)} \tag{2}$$

In case we consider the total contribution of the factor X_i to the output variance, we also have to consider the interactions of X_i with other factors, which accounts not only for the main effect, but also the higher-order effects. That will be the *total effect* of the factor X_i. Hence, *total index* S_{T_i} can be defined as shown in equation (3). Total effect will give, then, how much the output variance is reduced on average when factor X_i is fixed.

$$S_{T_i} = 1 - \frac{V_{\sim i}(Y)}{V(Y)} \tag{3}$$

In practice, when k is large, only the main effects and the total effects are computed, obtaining a good information on the model sensitivities. In addition, S_i and S_{Ti} are closely linked to a couple of extremely significant sensitivity settings in the calibration context: *factor fixing* and *factor prioritisation* (Ratto et al., 2007). *Factor fixing* refers to the identification of those input factors, if any, which have no influence on the model output and therefore can be fixed to any value within their feasible range, but with negligible implications on the output. *Factor prioritisation* describes the ordering of the input factors according to their relative influence on the model output (Sarrazin et al., 2016).

First-order index being zero, $S_i = 0$, is a necessary but insufficient condition to identify the factor X_i as non-relevant and fix it. In such case, the factor may be involved in interactions with other factors, so there might be higher-order terms (Saltelli et al., 2008). Instead, $S_i > 0$ is a good value to qualify a factor as influential, as a factor prioritisation setting.

On the other hand, total indices are suitable for the factor fixing setting (Saltelli et al., 2008), being $S_{T_i} = 0$ a necessary and sufficient condition in order to fix X_i as a noninfluential factor. If $S_{T_i} \cong 0$, then X_i can be fixed at any value within its range of uncertainty without appreciably affecting the value of the output variance $V(Y)$. As $S_{Ti} = 0.01$ is generally used as a threshold for factor fixing (Sarrazin et al., 2016), both obtained S_{T_i} and S_i values are rounded to the second decimal.

For additive models and under the assumption of orthogonal input factors, S_{Ti} and S_i are equal and the sum of all S_i (and thus all S_{Ti}) is 1. For non-additive models interactions exist: S_{Ti} is greater than S_i and the sum of all S_i is less than 1, and, also, the sum of all S_{Ti} is greater than 1. By analysing the difference between S_{Ti} and S_i, the impact of the interactions between parameter X_i and the other parameters can be determined.

For calculating both S_i and S_{T_i}, the procedure suggested by Saltelli (2002) has been used, at the cost of $N(k+2)$ simulations, being N the base sample. Samples are generated with the Latin Hypercube sampling method (McKay and Beckman, 1979). Although commonly suggested N value in literature is 1000, Sarrazin et al. (2016) found that high N values ($N >> 1000$) are necessary for sensitivity indices to converge. However, they found that much lower N is enough when the goal is factor prioritisation or fixing. As the objective of the article is factor prioritisation and factor fixing, a value of N=2000 is used and confidence intervals are calculated.

Confidence intervals for the sensitivity indices are estimated with the bootstrap technique (Efron, 1979). A confidence interval of 95% is given for the sensitivity indices, where limits are computed with the basic method (Davison and Hinkley, 1997). For that purpose, a number of 1000 replicates is considered enough (Archer et al., 1997).

2.2. Storm Water Management Model

SWMM is a dynamic rainfall-runoff simulation model used for single event or long-term (continuous) simulation, where LID units can be modelled and added to a certain subcatchment (Rossman and Huber, 2016a). Conceptually a generic LID unit can be represented by a number of vertical layers (Rossman, 2010), combined to create the various LID controls. PP type LID control combines Surface, Pavement, Soil, Storage and Drain layers (Figure 2), being Soil and Drain layers optional. In this article a square subcatchment of $100\,\mathrm{m}^2$ has been generated for the simulations, all occupied by a LID control of the PP type.

As illustrated in Figure 2, PP can receive water from precipitation (i) or inflows ($q0$) from other areas. That water on the surface can evaporate ($e1$), infiltrate to pavement layer ($f1$), or flow out from the pavement as runoff ($q1$). Water in the pavement layer can also evaporate ($e4$), or percolate to the soil layer ($f4$). Something similar happens in the soil layer beneath; water can percolate to storage layer ($f2$), or evaporate ($e2$). In the storage layer, water can exfiltrate to native soil ($f3$), evaporate ($e3$), or be directed to another area or conveyance through the drain ($q3$). In this article $q0$ will not be considered, and regarding the analysed outputs covered in Section 2.3.4, outflow from the PP will be the sum of $q1$ and $q3$.

The hydrologic performance of the LID control is modelled by solving

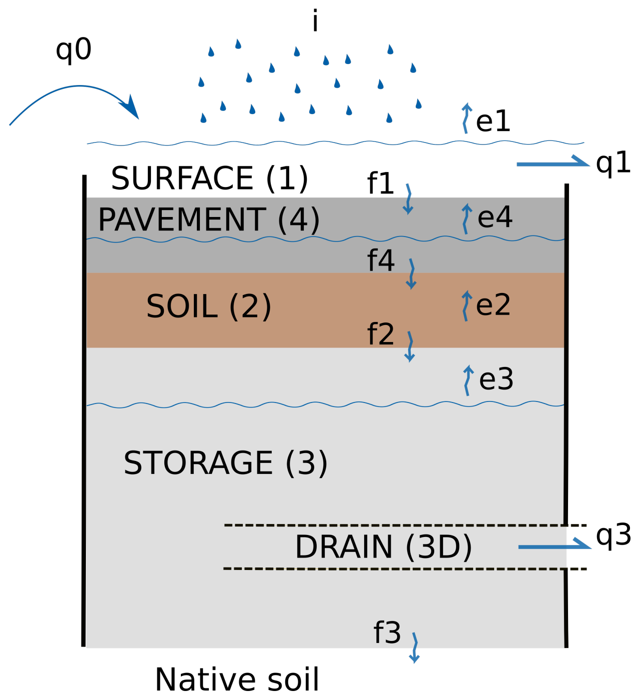

Figure 2: SWMM layers and flux terms for PP.

simple mass balance equations, given in the equations (4), (5), (6) and (7), that express the change in water volume in each layer over time as the difference between the inflow water flux rate and the outflow flux rate (Rossman, 2010). The flux terms (q, e, and f) in these equations are functions of the current water content in the various layers (d_i and θ_i) and specific site and soil characteristics. Both d_i and θ_i represent stored water, first one as depth (mm) and second one as moisture content (volume of water / total volume of soil). D_i are layer thicknesses and ϕ_i are layer porosities. The rest of parameters are specified in the Table 1, presented in Section 2.3.3, as they are model parameters.

$$\frac{d(d_1)}{dt} = i + q_0 - e_1 - f_1 - q_1 \tag{4}$$

$$D_4 \cdot (1 - F_4) \cdot \frac{d\theta_4}{dt} = f_1 - e_4 - f_4 \tag{5}$$

$$D_2 \cdot \frac{d\theta_2}{dt} = f_4 - e_2 - f_2 \tag{6}$$

$$\phi_3 \cdot \frac{d(d_3)}{dt} = f_2 - e_3 - f_3 - q_3 \tag{7}$$

Evaporation rates are calculated based on potential evaporation, $E_o(t)$, detailed in Section 2.3.1. Evaporation on the top layer or surface will be the minimum of $E_o(t)$ and available water. For layers below, evaporation will be the minimum of available water and the fraction of potential evaporation that did not materialise in the upper layers.

Water flow from surface is computed with Manning equation (8). Infiltration to pavement layer depends on available water volume on the surface layer, as shown in equation (9). Percolation from pavement layer is the pavement permeability, as shown in equation (10). Percolation from soil layer is calculated with equation (11), which will occur only if water content is higher than field capacity. In that case, percolation is modelled using Darcy's law. Flow from drain, equation (12), is computed as flow from an orifice, being h_3 the hydraulic head seen by the underdrain. Exfiltration to native soil is the seepage rate of the storage layer, as shown in equation (13).

$$q_1 = \frac{1.49 \cdot W \cdot S^{1/2}}{A \cdot n} \cdot (d_1 - D_1)^{5/3} \tag{8}$$

$$f_1 = i + q_0 + \frac{d_1}{\Delta t} \tag{9}$$

$$f_4 = K_4 \tag{10}$$

$$f_2 = \begin{cases} \text{if } \theta_2 > \theta_{fc} \text{ then,} & K_{2S} \cdot e^{(-HCO \cdot (\phi_2 - \theta_2))} \\ \text{if } \theta_2 \leq \theta_{fc} \text{ then,} & 0 \end{cases} \tag{11}$$

$$q_3 = C_{3D} \cdot (h_3)^{K_{3D}} \tag{12}$$

$$f_3 = K_{3S} \tag{13}$$

This set of equations can be solved numerically at each runoff time step to determine how an inflow hydrograph to the LID unit is converted into some combination of runoff hydrograph, sub-surface storage, sub-surface drainage, and infiltration into the surrounding native soil. Certain limitations are imposed on the above-mentioned water volumes, defined by the capacity of each layer in terms of available space to keep water, or present water volume. More details about the equations to compute moisture balance in each layer can be found on Rossman and Huber (2016b).

2.3. Model settings and sensitivity analysis

2.3.1. Climatological data

This study is undertaken with data gathered in Donostia/San Sebastián (Spain), located facing the Bay of Biscay, in an area with an Atlantic climate. Data from two weather stations has been gathered: one of them is Igeldo weather station (43°19′0″N, 2°0′0″W), with a large historical data, and the other one is Miramon weather station (43°17′20″N, 1°58′16″W), a newer weather station with 10 minutes time interval accessible data.

The sensitivity analysis is conducted studying the hydraulic response of the PP facing two kinds of events: short-term and long-term. As it is common for practitioners to check the performance of the network for a certain event, which is also a simple method for LID volumetric design purposes, a 100 years return period and 6 hour rainfall event has been considered for the short-term analysis (Woods Ballard et al., 2015). A synthetic single event is generated from data available at the Igeldo weather station. Based on the IDF curves representing a return period of 100 years, the precipitation depth for a 6 hours duration storm is 90.7 mm. The design storm has been set with the alternating block method (Chow, 2010), considering 15 minutes steps.

The aforementioned method does not address a continuous scenario, in which one storm may follow another, and the system may not have time to drain; henceforth, its potential to handle a new event will be limited. That is why the performance for the system facing continuous events should also be examined. As 5 years is considered the minimum period required for securing sensitivity analysis results that are stable in subcatchments (Shin et al., 2013), that period is also considered as sufficient for the defined subcatchment. For the long-term analysis, 5 years series recorded at the Miramon weather station have been gathered, both temperature and precipitation collected in 10-minutes intervals. Figure 3 shows gathered time series, but with daily precipitation and average daily temperature data to improve the visibility. Average rainfall is 1507 mm/year, with 196 days per year with measured rainfall, and average temperature is 14.2 °C.

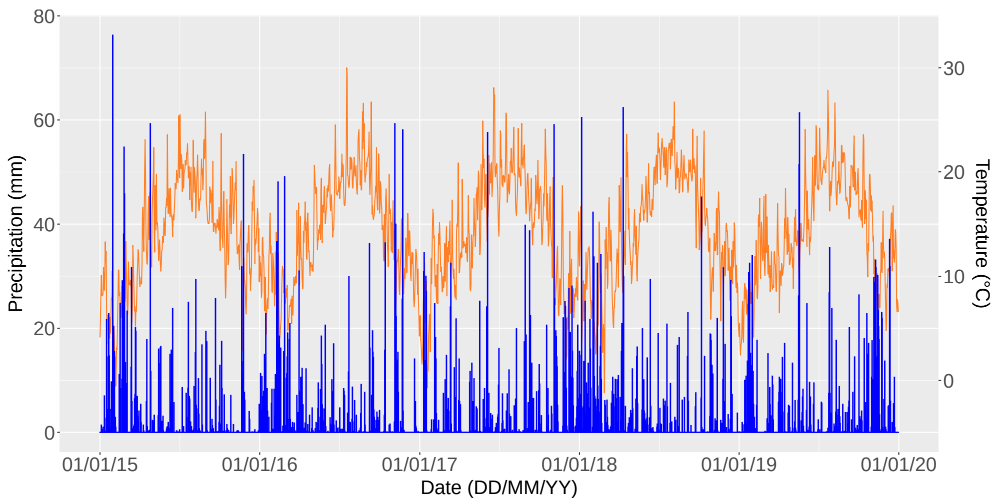

Figure 3: Daily precipitation (blue/left axis) and daily average temperature (brown/right axis) for the long-term modelling scenario.

Potential evaporation in the long-term is computed from daily maximum and minimum data, based on the Hargreaves method (Hargreaves and Samani, 1985) and the latitude. For the long-term, the considered time steps for computing runoff when modelling have been 2:30 minutes for Wet Weather and 10:00 minutes for Dry Weather. For the short-term, time step for both cases has been 1:00 minute. Reporting time step is 5:00 minutes for short-term and 10:00 minutes for long-term.

2.3.2. Selected optional layers for LID control

As mentioned before, there are two optional layers in the PP type LID control: soil layer and drain. The soil layer or bedding layer beneath the pavement, fine gravel or clean sand in practice, is a common layer for PICP in order to laying the pavers on a evener surface than the one given by bigger gravel. Although soil layer is not always placed (Randall et al., 2020;

Kayhanian et al., 2019; Tennis et al., 2004), soil layer has not been considered as an optional layer. Thus two cases are studied: one with Drain option deactivated, named as *SO* and, a second one with Drain activated, labelled as *SODR*.

2.3.3. Selected input parameters for LID control

The inputs or parameters given to SWMM, which are used to compute the mentioned water balances to get the outputs, are listed on the Table 1. The table also indicates which parameters have been used in the following SA. Vegetation Volume Fraction from the Surface layer, which refers to the volume occupied by stems and leaves over the surface (Rossman, 2015), has been excluded from the SA, as it is very unusual case in PPs (this parameter is general for all LID control types). Parameters that reduce permeability in the long-term, such as clogging factor, regeneration interval and regeneration fraction, have not been considered.

In the storage layer, the parameter that considers the reduction of the seepage rate has not been considered either: clogging factor. Finally, the parameters that control the opening and closing of the drain have not been considered: open level, closed level and control curve. All those values have been ignored while calculating PP performance.

Table 1 also gives the range for each parameter value while performing the SA, maximum and minimum are given, considering a uniform distribution. Most parameter ranges are taken from the SWMM manuals (Rossman, 2015; Rossman and Huber, 2016b). Some are modified, such as Surface Berm Height (SUbh) top value, which is set to 150 mm, as it is common value for the curb height which might work as a berm. Another revised value is Surface

Roughness (SUro), as values given by the manual are considered typical for traditional pavements. Therefore, as pervious pavements are more rough than traditional ones, unfinished concrete value of 0.02 is used as a high value for roughness (Chow, 1959). Another modified value is the Surface Slope (SUsl). A top value of 10% is selected, as it is not usual to design higher slopes, mainly because of accessibility issues. In Spain, for example, the different regional regulations do not exceed 8% in general, and allow slopes of up to 12% for ramps (Alonso López, 2010).

The Soil layer and its parameters are, probably, the most unknown to practitioners, since they are defined with soil parameters such as wilting point or suction head. Some Soil parameters are also changed, Soil Thickness (SOth) for example. In that sense, as mentioned in the introduction, it is considered that there is a wide variety of cross sections that can be modelled in many different ways. For that reason, a maximum thickness of 200 mm is considered (Woods Ballard et al., 2015). Field Capacity (SOfc) and Wilting Point (SOwp) are also modified, as it is considered that those materials may be clean gravel/sand type. Therefore, a 0.06/0.20 range is considered for the first parameter and 0.01/0.05 for the second one (Pardossi et al., 2009).

In the Storage layer, seepage rate is also modified, considering it up to 1000 mm/h (Woods Ballard et al., 2015). In the Drain layer, the Flow Coefficient (DRfc) is considered up to 1000 (Zhang and Guo, 2015). It should be noted that the Offset value from the drain layer is not given in mm, but as a percentage of the total thickness of the Storage layer.

Although SWMM contains some parameters related to the LID control in a subcatchment, such as Subcatchment Area, Surface Width per Unit,

Table 1: SWMM parameters for PP type LID control.

LAYER / Parameter	Symbol	*Code*	*Units*	*Min.*	*Max.*
SURFACE					
Berm Height[sa]	D_1	SUbh	mm	0	150
Vegetation Volume Frac.	$1 - \phi_1$	SUvf	-	0	0
Roughness[sa]	n	SUro	Manning n	0.01	0.02
Slope[sa]	S	SUsl	%	0	10
PAVEMENT					
Thickness[sa]	D_4	PAth	mm	60	250
Void Ratio[sa]	$\phi_4/(1-\phi_4)$	PAvr	Voids/Solids	0.3	0.8
Impervious Surf. Frac.[sa]	F_4	PAis	-	0	0.95
Permeability[sa]	K_4	PApe	mm/h	0.01	40000
Clogging Factor	-	PAcf	-	0	0
Regeneration Interval	-	PAri	days	0	0
Regeneration Fraction	-	PArf	-	0	0
SOIL					
Thickness[sa]	D_2	SOth	mm	0	200
Porosity[sa]	ϕ_2	SOpo	vol. frac.	0.25	0.35
Field Capacity[sa]	θ_{fc}	SOfc	vol. frac.	0.06	0.20
Wilting Point[sa]	θ_{wp}	SOwp	vol. frac.	0.01	0.05
Conductivity[sa]	K_{2S}	SOco	mm/h	100	800
Conductivity Slope[sa]	HCO	SOcs	-	20	60
Suction Head[sa]	ψ_2	SOsh	mm	40	120
STORAGE					
Thickness[sa]	D_3	STth	mm	100	1000
Void Ratio[sa]	$\phi_3/(1-\phi_3)$	STvr	Voids/Solids	0.2	0.8
Seepage Rate[sa]	K_{3S}	STsr	mm/h	0	1000
Clogging Factor	-	STcf	-	0	0
DRAIN					
Flow Coefficient[sa]	C_{3D}	DRfc	-	0	1000
Flow Exponent[sa]	K_{3D}	DRfe	-	0	30
Offset[sa]	D_{3D}	DRof	mm	0	100*
Open Level	-	DRol	mm	0	0
Closed Level	-	DRcl	mm	0	0
Control Curve	-	DRcc	-	-	-

*: this value is given as a percentage of Storage Thickness.
[sa]: included in the sensitivity analysis.

% Initially Saturated, % Impervious Area Treated and % Pervious Area Treated, these parameters have not been considered in the SA, since the study focused on studying specifically the LID control and its parameters.

2.3.4. Hydrological outputs and data treatment

When carrying out a sensitivity analysis it is essential to define its objective in advance, i.e. which variable or model result is going to be analysed. SA results may vary depending on targeted output: each target function is insensitive to some, often different, parameters, particularly for those models with more than a handful of parameters (Shin et al., 2013).

The aim of this study is to explore the impact of design parameters on the hydraulic response of the PP. To this end, the outputs analysed are those related with the generated outflow from the PP site: outflow volume and outflow peak. For that purpose, outflow will be the sum of q_1 and q_3 from Figure 2, that is, superficial runoff and drain outflow.

All outflow data managed by the PP, used to evaluate sensitivity indices, is obtained from the report file generated by SWMM. Data related to the volumes is read from the LID Performance Summary section. Data relative to peak flows is collected from the same file but, in this case, from the Node Inflow Summary, as runoff and drain flows are diverted in the model to a couple of nodes for that purpose.

By evaluating a total of two outputs across four cases, sixteen indices are calculated for each LID parameter: a first-order one (S_i) and a total effect one (S_{Ti}) for each parameter. As analysed input/output cases are multiple, values are compared graphically.

The data has been gathered with the version 5.1.015 of SWMM (EPA, 1971). The analysis of the data has been carried out using the open-source programming language R (R Core Team, 2020). For modelling purposes *swmmr* package has been used, which interfaces the SWMM with R (Leutnant et al., 2019). For the sensitivity analysis, the *sensitivity* package has been used (Iooss et al., 2020), and for sample generating the *pse* package (Chalom and Knegt Lopez de Prado, 2017).

3. Results and Discussion

The results are presented into several sections. First, some general data description is given. Later, (1) differences between short- and long-term are discussed, (2) the influence of the drain layer is analysed, and (3) differences between selected outputs are discussed. At the end, (4) global analysis is performed.

Although a total of 164 000 simulations are done across various cases while performing the global SA and, in addition, the 1-in-100 years storm is simulated for the short-term analysis, few outflow values are computed. On average, just 0.93% of the simulations produced any outflow. In particular, the short-term analysis created any outflow five times more than the long-term, which appears to be intuitive, since the short-term precipitation is higher. Something similar happened with the optional layers, SODR created outflow almost eight times the SO option did. That also appears to be intuitive, since active drainage layer allows underdrain flow. The most remarkable aspect of this data is that it shows how effective can PP be reducing the contribution to the stormwater network, no matter how the PP is designed. The reason for that is that rain intensity is usually lower than pavement permeability and its storage capacity allows infiltration to native soil before flow is diverted from the drain.

Once SA is performed, some S_i values are found to be close to zero but negative. That is consistent with previous findings, as Saltelli et al. (2008) described negative signs due to numerical errors in the estimates when analytical sensitivity indices are close to zero. In addition, obtained confidence intervals were very large in all modelling scenarios, as convergence was not obtained for calculated sensitivity indices. To avoid those negative values and high confidence intervals, sample size should be increased until convergence, which is considered unnecessary for factor fixing and prioritisation. Also, the methodology used to obtain confidence intervals yielded negative values or indices higher than one. As those are considered meaningless, those values are not represented on the figures.

Before proceeding with a global discussion considering all the cases, conducted at the end of this section, three previous analyses have been performed from the calculated indices. For those mentioned reviews, plots with values for first-order indices (S) and total effect indices (ST) are created. For that purpose, Table 2 is also built, giving the sum of all indices across cases. Values from that table will be discussed in the next sections. In addition, that table confirms that the model is nonadditive, as the sum of S_i is smaller than one for all cases. Also, the sum of S_{Ti} is greater than one for all considered cases.

3.1. Analysis of short- or long-term influence

Regarding to the analysis of storm length, some differences arise between short-term and long-term. The Figure 4 and values from Table 2 show that long-term outflows are much more influenced by single parameters, without considering any interactions. For the short-term, 4.5% of the variance can

Table 2: Sum of first-order indices, $\sum_{i=1}^{k} S_i$, and total-effect indices, $\sum_{i=1}^{k} S_{Ti}$, for each modelling scenario.

INPUT	Short-term (6 hours)				Long-term (5 years)			
	SO		SODR		SO		SODR	
OUTPUT	Vol.	Peak	Vol.	Peak	Vol.	Peak	Vol.	Peak
$\sum_{i=1}^{k} S_i$	0.12	0.06	0.00	0.00	0.66	0.44	0.63	0.21
$\sum_{i=1}^{k} S_{Ti}$	2.42	2.81	9.84	9.84	1.34	1.78	1.76	2.63

be explained, on average, by one parameter (SOth). On the other hand, for the long-term outflow 48.5% of its variance can be explained, on average, by two variables (SOth and STsr). In summary, parameter interaction plays a significant role on the short-term.

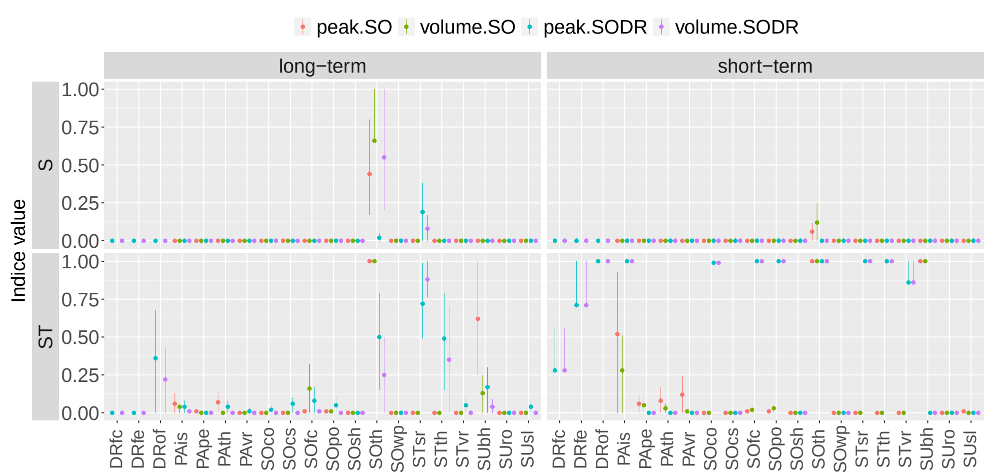

Figure 4: Estimated total (ST) and first-order (S) effects with their confidence intervals for the long (left) and short-term (right) modelling scenarios. Different colours are shown for scenarios including (SODR) and excluding (SO) the effects of drain and measuring outflow peak or volume.

3.2. Analysis of drain influence

If the sensitivity indices are examined according to whether the drain layer is active or not, the individual influence of parameters is similar to the previous case. As shown in Figure 5 and values from Table 2, outflow variance in the SO case is explained on, as average, by one variable (SOth) in a 32%, while in the SODR case is explained by two variables (SOth and STsr) in a 21%. That means that interactions are more relevant when Drain layer is active, which seems reasonable, as outflow is also controlled by the drain parameters, and, overall, influence of the SOth is reduced.

In that sense, the number of parameters that may be fixed without affecting the outflow, with a $S_T \approx 0$, increases in the SO case. However, it is interesting how these parameters differ from case to case. For the SO case, all parameters other than SOth and SOfc may be fixed in the Soil layer. On the contrary, for SODR case, almost all parameters may be fixed in the Pavement layer. That shows that when Drain layer is active, other soil parameters different from Thickness have also influence in the outflow, which also accounts for drain flow. But, when Drain layer is not active and outflow accounts just for runoff, Soil layer parameters loose its influence and Pavement layer parameters influence is notable. That appears to be intuitive, since pavement parameters control runoff or at what extent there will be infiltration to the layers below.

3.3. Analysis of peak or volume or peak

With regard to the output values, Figure 6 and values from Table 2 show that, on average, 35.2% of the outflow variance is explained by two parameters for the outflow volume, but that value decreases to the 18.8%

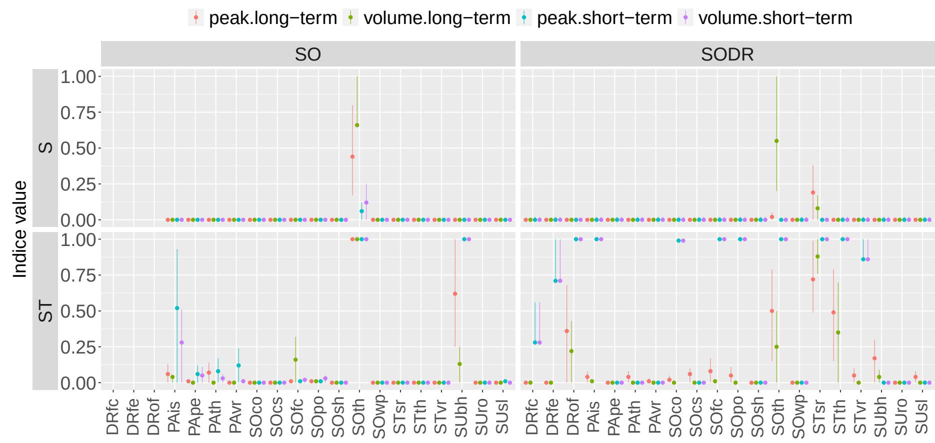

Figure 5: Estimated total (ST) and first-order (S) effects with their confidence intervals for scenarios excluding (SO), on the left, and including (SODR), on the right, the effects of drain. Different colours are shown for scenarios considering the long- or short-term modelling and measuring outflow peak or volume).

when the analysed output is the peak flow, while the variables remain the same (SOth and STsr). Also, interactions play a smaller role on the volume outflow than in the peak flow. It is also interesting to see how the number of values which can be fixed without affecting the output is higher for the runoff volume. For runoff peak the are three parameters with a $S_T \approx 0$, while for the volume there are six, which includes all the previous three.

3.4. General analysis

Finally, all cases are compared at once in Figure 7, which is also used to identify the most important parameters and those that can be neglected or fixed when calibrating the model, no matter what input/output case we consider. Those parameters are summarised in Table 3.

The graph clearly shows that only two parameters have a influence by

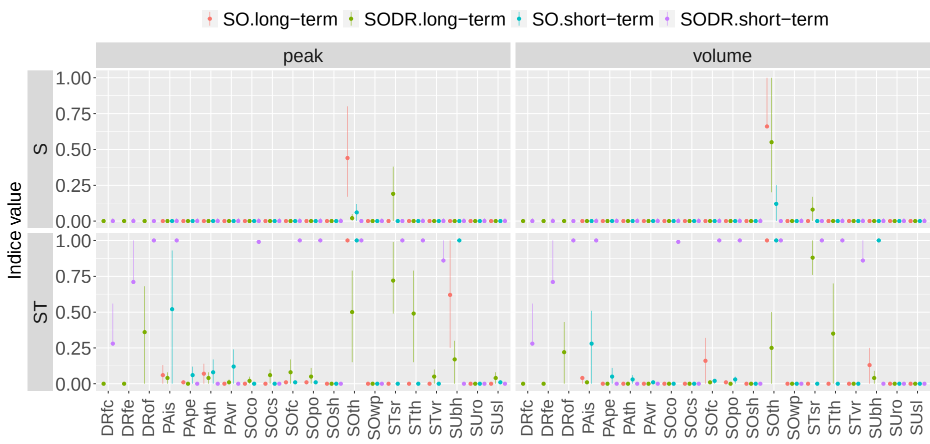

Figure 6: Estimated total (ST) and first-order (S) effects with their confidence intervals for scenarios measuring outflow peak (left) and outflow volume (right). Different colours are shown for scenarios including (SODR) and excluding (SO) the effects of drain and considering the short- or long-term modelling.

themselves on the evaluated outputs. SOth and STsr alone can explain, as average, 26.5% of the output variance. On the contrary, there are clearly three parameters that do not affect the output variance: SOsh, SOwp and SUro. First two parameters will be the most obvious candidates for the influential ones, and last three will be set as the ones without any influence.

If examined by layer, surface parameters have no influence individually. On the contrary, SUbh presents high interactions with other parameters, thus, it can be considered as the most influential parameter of this layer. On the other hand, SUsl presents quite low interactions in just one case, so it will be considered as having low influence. It seems consistent SUbh being the most influential parameter, as it can restrict the output level and, consequently, the generated runoff and infiltration to layers below.

With regard to the Pavement layer, something similar happens with the individual influence, since all parameters show a first order index equal to zero. If total indices are examined and, thus, interactions, PAis is clearly the most influential parameter. The other three parameters present moderate interactions, enough not to be considered as non influential. To rank the other three parameters, the number of cases with the total effect index greater than zero and its value are checked. Hence, the most influential parameter is PAth, followed by PApe and, finally, PAvr. None has been considered as non influential at all, although PAvr could be considered as such in most of the cases. Again, it seems reasonable PAis being the most influential, as it controls the open space that water has on surface to penetrate into the pavement section before other parameters can have any influence.

The soil layer, the one with highest number of parameters, contains the most influential parameter by itself alone: SOth. This layer has also two parameters with no influence in the output: SOsh and SOwp. There is a third one, SOcs, that presents low interactions in just one case. As the number of parameters is high in this layer, this last parameter will also be considered as non-influential. Other three parameters show moderate interactions, variable over cases: SOfc clearly interacts more than SOpo and SOco. In this layer, as opposed to the other layers, there is no a clear physical explanation for SOth being the most influential one. An explanation may be that the layer thickness controls how water can percolate into lower layers and, thus, controls the amount of water on the surface that can turn into runoff.

The storage layer contains the second most influencing parameter overall: STsr. However, its individual influence arises when the Drain layer is active.

The other two storage parameters present moderate and high interactions, so they can not be fixed. These interactions are also for the activated Drain layer option, indicating that storage layer parameters have influence, mainly, in the drain outflow. STth would be the most influential of both, and STvr the least. Here, again, it seems reasonable STsr to be the most influential, as it would control outflow and, thus, water level on the layer, before there is outflow from the drain and other two parameters can have its role.

The last layer, the only one considered as optional, has no parameters influencing by themselves. On the contrary, all parameters show interactions. The most influential would be DRof, followed by DRfe and DRfc. Here, it also seems a reasonable outcome, as the drain offset controls the flow presence on the drain.

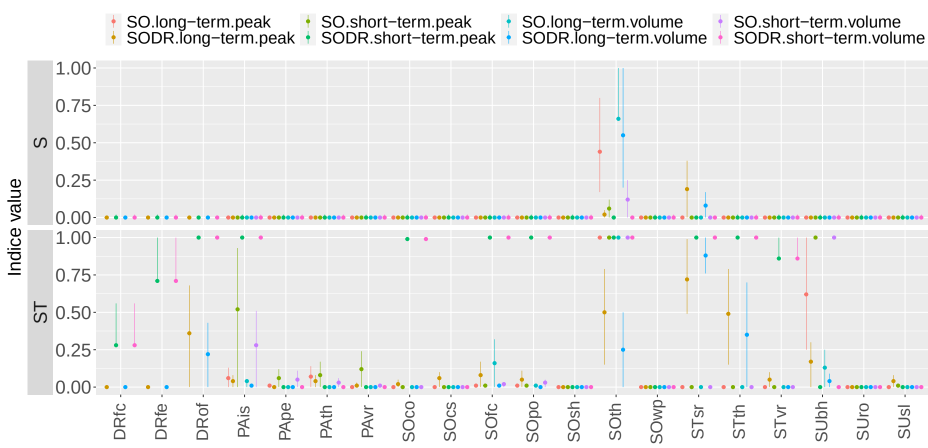

Figure 7: Estimated total (ST) and first-order (S) effects with their confidence intervals for all considered scenarios. Different colours are shown for scenarios including (SODR) and excluding (SO) the effects of drain, scenarios with long- or short-term modelling, and scenarios measuring outflow peak or volume.

Table 3 summarises, for each layer, the most influential parameters, those with little influence and those that its value can be fixed. The table is the main objective of this article, and will provide practitioners calibrating a real pavement, or designing a new one, a helpful tool to focus their efforts on the most important parameters (Figure 7 can also be used for that purpose). The data is given as a general tool for runoff control purposes, no matter if the simulation is done in the long term/short term or if Drain optional layer is checked. The most influential parameters are given in the first column, and those parameters that have less influence, including interactions with other parameters, are given in the second one. The last column gives those parameters which value can be fixed and influence neglected. It is recommended to start with the most influential one and, if necessary, to follow with those who have less influence.

Table 3: Factors influence for PP type LID in SWMM.

LAYER	Most influential	Low influence	No influence
Surface	(1) SUbh	(2) SUsl	SUro
Pavement	(1) PAis	(2) PAth (3) PApe (4) PAvr	-
Soil	(1) SOth	(2) SOfc (3) SOpo (4) SOco	SOsh, SOwp, SOcs
Storage	(1) STsr	(2) STth (3) STvr	-
Drain	(1) DRof	(2) DRfe (3) DRfc	-

As mentioned in the introduction, Randall et al. (2020) are the only ones that studied PP, but they performed a One At a Time (OAT) SA for three cross-sections, focusing on their study, but not as a general tool. They performed the SA for a short-term event, and studied the underdrain flow, peak and volume, without considering the runoff. However, SOth is not identified as an influential parameter. If values from Figure 4 are analysed in detail, it can be seen that for the short-term and SODR case none of the parameters has $S_i > 0$, not even the SOth; that may explain the difference. Rest of the parameters seem to fit well with findings from Randall et al. (2020). Therefore, their findings are in line with the values obtained here.

4. Conclusion

Although PP is studied here and some other LID types previously were, it would be advisable, for future research, to analyse the sensitivity of LID modules that have not yet been studied (rain barrel, rooftoop disconnection, rain garden and vegetative swale).

The parameters that reduce the permeability of the different layers have not been analysed in this article, as that case may be related to the ageing of the pavement. It would be interesting to study how clogging may affect to other parameters. Similarly, the parameters associated with the assignment of LIDs to the subcatchment have not been studied, as those are the same for all LID types. Thus, it would also be interesting to examine their influence on the model output.

Moreover, as the soil layer parameters are quite unknown, particularly when applied to PPs, its properties should be further investigated, as it can not be characterised as a natural soil. Also, the study has been carried out with the data associated to a certain climate, so other rainfall could yield different results. It is recommended to study the influence of other rainfall regimes in the model.

Results show that, in general and regardless the type of storm analysed or whether the drain is active, there are a few parameters that control the value of the outflow from a PP site. There are certain differences among cases but the influential/negligible parameters are similar. Consequently, the most influential ones are berm height, impervious surface fraction of pavement, soil thickness, storage seepage rate and drain offset. On the contrary, surface roughness, soil suction head, soil wilting point and soil conductivity slope have negligible influence on the outflow.

Thus, the most sensitive and non-influential SWMM parameters corresponding to the PP type LID control are identified in this article. Although further research is needed, the parameter list given in this article may still be a helpful tool for practitioners while calibrating a PP, as data is given as a general tool, not specific to a case, considering long-term performance and most useful parameters for urban stormwater design.

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