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1 **Field validation of a physically-based model for bioretention**
2 **systems**

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25

26 *(From Introduction to Conclusions - 5457 words - 29500 characters)*

27

28 **Abstract**

29

30 Bioretention systems are increasingly used worldwide to mitigate the impacts of urban
31 stormwater runoff on the water cycle. Being able to accurately model physical processes
32 occurring within these systems is critical to their design and to being able to predict their
33 performance. Most popular urban hydrological models must now integrate a low impact
34 development (LID) toolbox to keep up with current practices. We aimed to develop and test
35 a generic model of bioretention systems that can serve as a targeted compromise between
36 oversimplification without any physical basis, on the one hand, and physical soundness
37 requiring a large number of parameters for calibration, on the other. The model accounts for
38 evapotranspiration, overflow, infiltration into the filter (single permeability behavior),
39 exfiltration to surrounding soils, along with underdrain discharge. The model was tested
40 against field data from a monitored bioretention basin in Melbourne, Australia. Based on 22
41 rainfall events, results showed that the simulated underdrain outflow rates and their
42 temporal dynamic were well replicated (for 20 rainfall events, median NSE = 0.74, median
43 PBIAS = -22%, median RMSE = 0.48 l/s). Despite good performance for outflow rates, there
44 was a discrepancy observed in magnitude between simulated and measured water levels
45 within the bioretention basin. The model therefore seems a useful first step towards the
46 design of a user-friendly model for assessing both performance and impact of bioretention
47 basins for catchment-scale flow regime management.

48

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50 **Key words:** Bioretention models, LID toolbox, WSUD, stormwater

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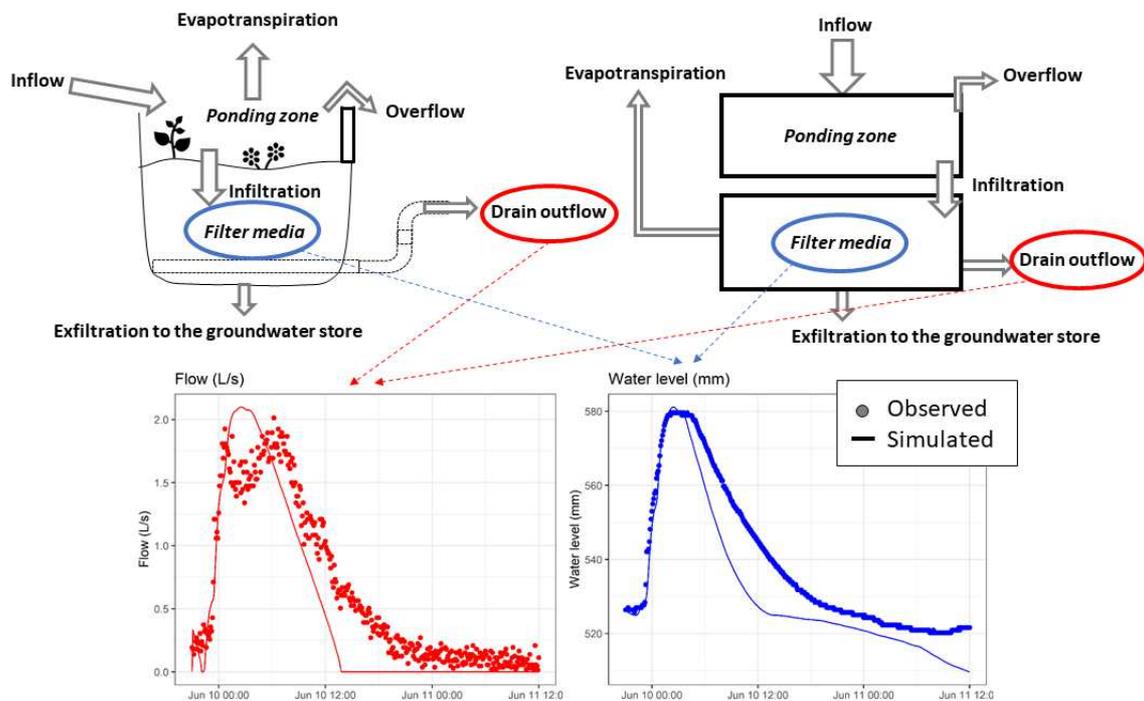
52 **Highlights:**

- 53 • We developed a hydrologic model for bioretention basins for modeling outflow rates.
- 54 • The model was able to replicate piped outflows from a real case study with two parameters needed for calibration.
- 55
- 56 • The accurate modeling of water level dynamics within the bioretention filter requires
- 57 additional soil physical parameters and was not well replicated.

58

59 **Graphical abstract**

60



61

62

63

64 **1. Introduction**

65

66 To mitigate the impacts of urbanization on the flow regimes and water quality of water
67 bodies (Walsh et al., 2012), bioretention basins are increasingly used as part of a suite of
68 stormwater control measures (SCMs). Bioretention basins are landscaped depressions filled
69 with sand and gravel, often vegetated, that are designed to receive urban runoff (from roofs,
70 roads, etc.). They provide storage and allow urban runoff to be released to the atmosphere
71 by evapotranspiration and infiltrated in native soils rather than discharged in piped networks
72 to urban streams or other receiving waters. As such, bioretention basins are extremely
73 efficient at reducing urban runoff peak flows, stormwater volumes and pollutants loads (Liu
74 et al., 2014; Roy-Poirier et al., 2010). Their application aims to restore lost fluxes of the
75 water balance (evapotranspiration, infiltration) and to reduce stormwater runoff caused by
76 creation of impervious areas and hydraulically-efficient drainage systems (Burns et al., 2012).
77 Modelling the performance of bioretention basins is, however, a challenge, as physical
78 mechanisms involved in these systems are complex. These requirements can often preclude
79 their use by decision-makers, designers and practitioners, meaning that there is a need for
80 models which can be simply but reliably calibrated using relatively easy-to-collect monitoring
81 data. A model which is physically-based, yet easy to calibrate, could be attractive for urban
82 water management practitioners in current and future cities.

83

84 A wide range of tools exist to model Low Impact Development (LID) structures (Elliott and
85 Trowsdale, 2007). The popular SWMM model includes a very flexible landscape-scale
86 infiltration module, offering a choice of Hortonian, Green-Ampt or Curve-Number infiltration
87 (Rossman, Lewis A., 2010; Rossman, Lewis A, 2010). The LID module in SWMM is based on

88 the Green-Ampt infiltration from the surface into the filter media, followed by Darcy's flow
89 through the porous media below, with subsequent infiltration to groundwater assumed to
90 be constant. To model retention in green roofs, Kasmin et al. (2010) present a conceptual
91 process-based model, where the soil is described as a store with different soil moisture
92 thresholds that drive hydrological processes (e.g. runoff produced when soil moisture is
93 higher than field capacity). DRAINMOD is used extensively to model bioretention systems:
94 infiltration is modeled with the Green-Ampt equation (Skaggs, 1980, 1985) and requires the
95 user to specify the soil-water characteristic curve and saturated hydraulic conductivity
96 (Brown et al., 2013). DRAINMOD was recently adapted to the urban case (Lisenbee et al.,
97 2020). Drainage is modeled with the Hooghoudt's equation, taking into account lateral
98 hydraulic conductivity and properties of the underdrain (particularly spacing and radius). In
99 Australia, MUSIC is the industry standard to model bioretention basins and other
100 Stormwater Control Measures (eWater, 2014, 2020). Infiltration within bioretention basins is
101 described in MUSIC by Darcy's equation, accounting for impacts of soil texture and moisture,
102 with infiltration calculated from both the base and sides, while underdrain flow is calculated
103 from Darcy's flow through the porous media, again accounting for texture and degree of
104 saturation. Richards' equation, that combines mass conservation and Darcy's equation
105 (Richards, 1931; van Genuchten, 1980), was used to model flow in bioretention cells to
106 predict peak flow and volume reduction by He and Davis (2011). Other models used the
107 Green-Ampt equations, e.g. Gülbaz and Kazezyılmaz-Alhan (2017).

108

109 In general terms, bioretention models may be separated in two groups. The first group is
110 made up of models that have no extensive physical basis and are mostly designed
111 statistically for a given experimental site, thus requiring a low number of parameters to

112 implement. However, these models are often case-specific, being difficult to extrapolate to
113 other sites and having limited predictive capabilities. Conversely, the second group is
114 composed of more complex models, that are based on the modeling of physical processes,
115 and usually require significant effort for calibration (Alamdari and Sample, 2019) or access to
116 specific soil parameters which are complicated to estimate (such as the soil water retention
117 curve or the unsaturated hydraulic conductivity). There is thus a need for a third option:
118 models that are simple to calibrate while offering a satisfying level of consistency with
119 regards to the physics of water infiltration in the bioretention systems, the use of more
120 sophisticated models not systematically improving modelling results, since more parameters
121 are needed, and calibration becomes more difficult (Mourad et al., 2005) and thus less likely
122 to be undertaken by decision-makers and system designers.

123

124 The aim of this study was therefore to develop and test a simplified, physically-based model
125 requiring low effort for calibration and capturing the hydraulic dynamic of bioretention
126 systems. We report the development and testing of a physically-based hydrologic model
127 against data obtained from a monitored bioretention basin (Wicks Reserve Bioretention
128 system). The modelling approach describes the whole bioretention system as a series of
129 reservoirs storing and exchanging water fluxes. The approach includes consideration of mass
130 conservation (continuity equation), Darcy's equation for the implementation of infiltration
131 fluxes into the system and the soil below, orifice equation for the underdrain, with the
132 computation of evapotranspiration, allowing the prediction of exchanges between the
133 reservoirs, and thus the water level in the filter (body of the bioretention system) and the
134 outflow rates. Therefore, we present a new model that explicitly accounts for physical
135 processes (soil water storage, vertical gravity-driven infiltration, exfiltration, respect of mass

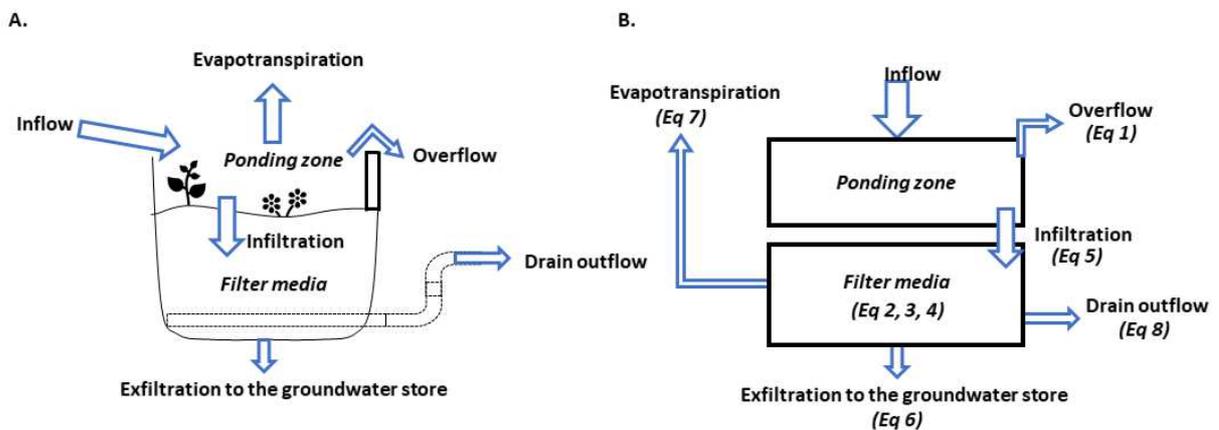
136 balance) under unsteady flow conditions, to predict the outflow performance of
137 bioretention systems. A key objective was to provide explicit and simplified formulation of
138 existing modelling approaches and equations in order to create a physically-based model.

139

140 **2. Methods**

141 **2.1. Model development**

142 The model is a physically-based representation of bioretention basins, based on reservoirs or
143 storages in series, accounting for the water balance between storages and water fluxes
144 between storages (Figure 1). All equations presented below were discretised using a first
145 order, explicit numerical scheme, considering a fixed 6 minutes timestep, to fit with
146 observed data. The complete algorithm and computation code (R scripts) are available as
147 Supplementary material and the dataset used is publicly shared on the platform Zenodo
148 (Bonneau et al. (2021) <http://doi.org/10.5281/zenodo.4717453>).



149
150 *Figure 1: Conceptual representation of the model*

151 *First reservoir: the ponding zone*

152 The first reservoir corresponds to the ponding zone or the surface storage area. It is
153 assumed to be a rectangular empty box (Figure 1). It receives the entering water fluxes that
154 are routed to the bio-infiltration system (Inflow). The inflow hydrograph leads to water level
155 in the ponding zone which acts as the upstream boundary condition.

156

157 This reservoir has a maximum capacity. When the water level exceeds a given threshold, an
158 overflow pit or weir diverts excess water out of the surface storage. In the model, a
159 threshold level is set by the user so that when the water level in the surface storage is
160 greater than this threshold, water is diverted producing an overflow rate computed by mass
161 balance consideration (Eq. 1).

$$162 \quad \text{if } h_{pond} < h_{weir}, Q_{ovf} = 0$$

$$163 \quad \text{Otherwise, } Q_{ovf} = Q_{in} - Q_{inf} \text{ (Eq. 1)}$$

164 Where h_{pond} is the water level in the surface storage, h_{weir} the height of the overflow
165 weir, Q_{ovf} the overflow rate, Q_{in} the inflow entering the ponding zone, Q_{inf} flux of water
166 infiltrating into the filter below.

167

168 *Second reservoir: the filter of the bioretention system:*

169 The second reservoir represents the filter that constitutes the main body of the bioretention
170 system (Figure 1). The filter receives the infiltration flux from the surface storage, and loses
171 water due to evapotranspiration, infiltration into the subsoils and to the outflow pipe
172 collected by an underdrain.

173

174 The infiltration from the ponding zone into the filter was modelled using a Darcian approach,
175 which is simple and commonly used to compute water fluxes in porous media (Bear, 1972).

176 The van Genuchten (1980) and Mualem (1976) models are among the most widely used for
177 the water retention and the unsaturated hydraulic conductivity functions and read as
178 follows (Eq. 2):

179
$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} = (1 + (\alpha h)^{1/(1-m)})^{-m} \text{ (Eq. 2a)}$$

180
$$K(S_e) = K_s S_e^\tau \left[1 - \left(1 - (S_e)^{\frac{1}{m}} \right)^m \right]^2 \text{ (Eq. 2b)}$$

181 Where S_e is the saturation degree, θ the volumetric water content, θ_s the saturated
 182 volumetric water content and θ_r is the residual water content, α a fitting parameter related
 183 to water pressure head; m ($m = 0.5$ for coarse soils, with the sand/gravels used for the filter
 184 and drainage layer) and τ ($\tau = 0.5$, default values for tortuosity) are shape parameters, K is
 185 the unsaturated hydraulic conductivity (m s^{-1}), K_s the saturated hydraulic conductivity (m s^{-1}).

186

187 To diminish the number of parameters in the model, some simplifications were proposed, as
 188 described below. The behaviour of the filter media was simplified by considering that it
 189 behaves like coarse material with a stepwise water retention function, as mostly considered
 190 for coarse media (Lassabatere et al., 2021). In that case, the water profile takes the shape of
 191 a step function, with saturated conditions below the height of water and dry conditions
 192 above. Eq. 2a is then replaced with a stepwise function and the parameter α is no longer
 193 needed. Considering a stepwise profile, the average saturation degree can be linked to the
 194 height of water in the filter media (Eq. 3):

195
$$\bar{S}_e = \frac{F}{F_{max}} \text{ (Eq. 3)}$$

196 Where \bar{S}_e is the average saturation degree at any time, F the height of water in the filter,
 197 i.e., the positive hydraulic head from the bottom of the filter, and F_{max} represents the total
 198 thickness of the filter layer. For simplicity, the term 'filter layer' is considered hereafter to

199 include the drainage layer. The hydraulic conductivity was then derived by applying the
 200 Mualem model (Eq. 2b) to the average saturation-degree, leading to the following
 201 expression for the unsaturated hydraulic conductivity:

$$202 \quad K\left(\frac{F_{i-1}}{F_{max}}\right) = Ks\left(\frac{F_{i-1}}{F_{max}}\right)^\tau \left[1 - \left(1 - \left(\frac{F_{i-1}}{F_{max}}\right)^{\frac{1}{m}}\right)^m\right]^2 \quad (Eq. 4)$$

203 We considered at any time i , the previous saturation degree $\bar{S}_{e_{i-1}} = \frac{F_{i-1}}{F_{max}}$. Note that the
 204 application of Darcy's equation allowed the quantification of the infiltrating flux rate by
 205 multiplying the unsaturated hydraulic conductivity (Eq. 4) with the hydraulic gradient.
 206 However, during the considered time step, no more than the volume of water available in
 207 the surface storage can infiltrate. In addition, no more than the volume available in the filter
 208 can be filled by the infiltrating water. These two conditions impose two limitations (Eq 5b.
 209 and 5c.). Finally, the infiltration rate into the filter media was obtained using the following
 210 equation (Eq. 5):

$$211 \quad Q_{inf,i} = \min \left(\begin{array}{l} \frac{F_{max} - F_{i-1} + h_{pond,i-1}}{F_{max}} K\left(\frac{F_{i-1}}{F_{max}}\right) A \quad (Eq. 5. a.) \\ (F_{max} - F_{i-1}) \frac{A}{\Delta t} \eta_f + \sum Q_{outs,i} \quad (Eq. 5. b.) \\ h_{pond,i-1} \times \frac{A}{\Delta t} + Q_{in,i} \quad (Eq. 5. c.) \end{array} \right)$$

212 where A is the mean area of the bottom of the ponding store, Δt is the time step, η_f is the
 213 mean porosity of the filter layer, $Q_{in,i}$ is the observed inlet flow rate at the time step i and
 214 $\sum Q_{outs,i}$ the sum of all outflows from the filter media at the time step i (in this case
 215 underdrain outflow, evapotranspiration and exfiltration to the native soil). Eq 5.a. in the
 216 function "min" corresponds to the application of Darcy's law, assuming the hydraulic
 217 conductivity detailed in equation (Eq. 4). Eq 5.b. and Eq 5.c. were set to respect the mass
 218 balance of the system. Eq 5.b. enables computation of infiltration rate when the storage

219 capacity within the filter limits the amount of water that could infiltrate (typically at the end
220 of an event). Eq 5.c. enables computation of infiltration rates when all the ponded water can
221 infiltrate during the time step i , typically at the start of an event with dry initial conditions.

222

223 The remaining fluxes were computed as follows. The exfiltration of water by infiltration into
224 the surrounding native soil was computed as a function of its hydraulic conductivity and the
225 wetted surface of the filter:

$$226 \quad Q_{exf} = K_{s\ inf} S_{wet} \text{ (Eq. 6)}$$

227 Where $K_{s\ inf}$ is the saturated hydraulic conductivity of the surrounding soil and S_{wet} is the
228 wetted area of the filter storage, i.e., the contact surface between water and the
229 surrounding soil. The flow in the native soil was then considered gravity-driven without
230 capillarity-driven infiltration.

231

232 The evapotranspiration resulting from plant root systems developed in the filter was
233 calculated from potential evapotranspiration (thus assuming a crop factor of 1.0) and
234 modulated with a linear function between the wilting point and field capacity (Eq. 7)
235 (Francés, 2008; Van der Lee and Gehrels, 1990):

$$236 \quad \text{if } \theta < \theta_w, Q_{etr} = 0$$

$$237 \quad \text{if } \theta_w < \theta < \theta_{fc}, Q_{etr} = \frac{\theta - \theta_w}{\theta_{fc} - \theta_w} Q_{etp}$$

$$238 \quad \text{if } \theta > \theta_{fc}, Q_{etr} = Q_{etp} \quad \text{(Eq. 7)}$$

239 Where θ_w and θ_{fc} are the wilting point and the field capacity, respectively, taken as usual
240 valued for sandy soils (FAWB, 2015), Q_{etr} is the real evapotranspiration rate and Q_{etp} the
241 potential evapotranspiration rate, sourced from a nearby meteorological station of the

242 Australian Bureau of Meteorology (Station 086266, Lat -37.87, Lon 145.35, calculated with
243 the Morton method, from the SILO database)(BoM, 2021; SILO, 2020).

244

245 Lastly, the outflow collected by the underdrain was computed with an orifice equation (thus
246 assuming the pipe itself does not limit flow), according to Eq. (8):

247
$$Q_{out,i} = C_{out}\sqrt{2gH} \text{ (Eq 8)}$$

248 Where C_{out} is an orifice coefficient to be calibrated, g the acceleration due to gravity and H
249 the difference between water level in the filter and the level of the underdrain orifice (Figure
250 1).

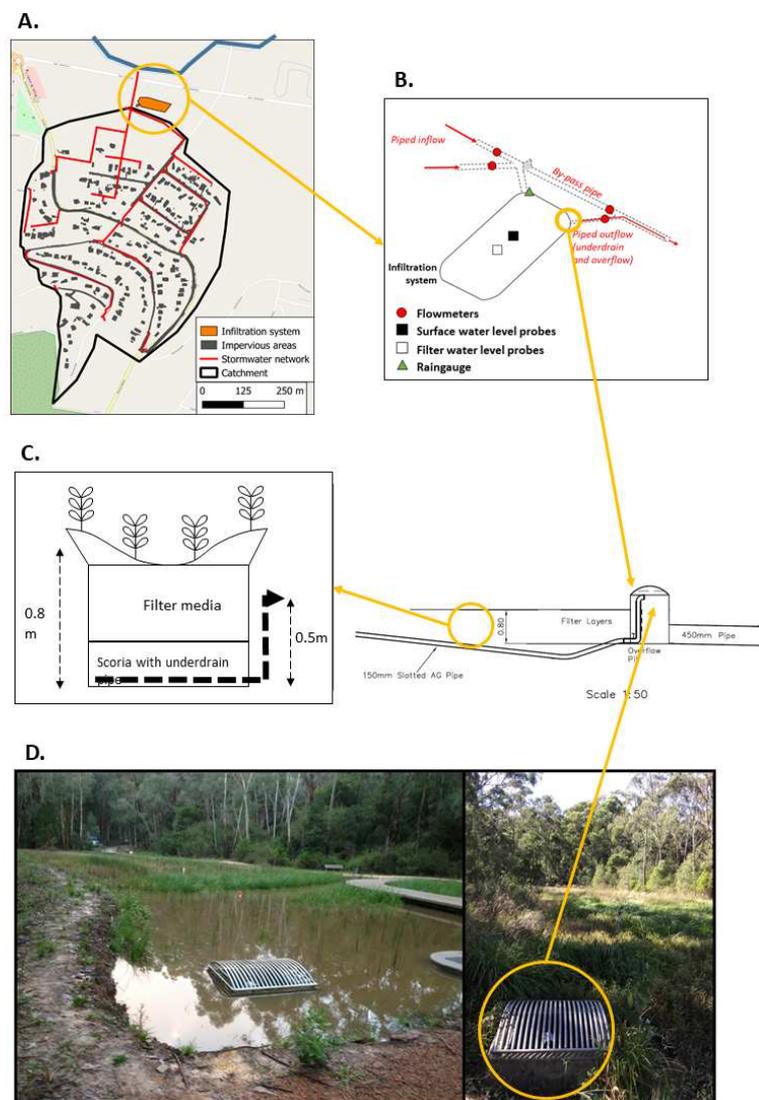
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252 2.2. Case study

253 2.2.1. Bioretention basin and catchment description

254 Wicks Reserve Bioretention Basin (hereafter referred to as “the basin”) is located in the
255 eastern suburbs of Melbourne, Australia (Bonneau et al., 2018). Stormwater enters the basin
256 by two stormwater pipes draining a combined 5 ha of impervious areas (estimated using
257 geographic information provided by the local municipality, and corroborated with rainfall-
258 runoff data) connected to a conventional, separate stormwater network, in a 33-ha
259 residential catchment. The catchment responds to rainfall quickly, with flow in pipes
260 observed around 30-45 minutes after rainfall. At the location of the basin, groundwater is
261 deeper than 4 m below the surface. The basin is 1800 m² in area, and on average 0.8 m deep
262 (350 mm loamy sand-based filtration media overlaying 300 mm of 20 mm scoria gravel, with
263 three 50 mm deep transition layers - medium-fine sand, coarse sand and 7-10 mm gravel - in
264 between them). There is a slotted underdrain at the base of the infiltration system, which
265 discharges through an elevated orifice in a discharge pit. The underdrain is connected back
266 to the stormwater network (“Outlet”). The orifice is elevated by 500 mm from the invert of
267 the basin, meaning that the bottom 500 mm acts as a ‘saturated zone’, with discharge below
268 this depth occurring only through infiltration (Figure 2). Above this depth both infiltration
269 and underdrain discharge may occur. The hydraulic conductivity of the surrounding native
270 soil was measured by fitting recession events (water level drop in the filter) and confirmed
271 with in-situ rising stage slug test with the Bouwer Rice method and found to be quite low,
272 around 1 mm hour⁻¹ or $2.8 \times 10^{-7} \text{ m s}^{-1}$. Large flows (> 200 L/s) are diverted from the basin
273 into a bypass pipe via a weir (“Bypass pipe”) immediately upstream of the basin, to ensure
274 excessively large flows do not damage the basin surface or vegetation.

275 The runoff from the basin's catchment is conveyed in two stormwater drains (Figure 2) and
 276 the inlet flow passes through a Gross Pollutant Trap (GPT) and a sedimentation pond before
 277 flowing onto the filter area of the bioretention basin. Indeed, the presence of the pond and
 278 the GPT delays inflow getting into the bioretention basin. In the model, we inserted a linear
 279 reservoir with a lag time of 15 min (assessed thanks to site observations and knowledge of
 280 the system) to account for the delay and the transformation of the inflow hydrograph due to
 281 GPT and sedimentation pond.



282

283 *Figure 2: A: Map of the catchment feeding the bioretention basin (source: Bonneau et al.,*
 284 *2020) B: Monitoring system. C: Transect of the filter of Wicks Reserve Bioretention basin D:*
 285 *Photos of the basin (sourcre: Bonneau et al., 2020).*

286

287 2.2.2. Monitoring and data presentation

288 The basin was monitored using four Sigma 950 flowmeters, one in each inlet pipe, and one in
289 each of the bypass and outlet pipes (Figure 2), so that inflow to the basin and outflow
290 through the underdrain could be measured and compared. Flow velocity was measured with
291 a Doppler probe and water level with a pressure diaphragm. Small weirs were built in pipes
292 to ensure the probes remained submerged. The flowmeters were manually calibrated:
293 manual flow measurements were performed regularly for high and low flows to obtain the
294 best relationship between the actual flow and the probe values (flow rate, level, velocity).
295 Data were collected from March 2013 to September 2016 (Bonneau et al., 2020). In addition,
296 water levels in the ponding zone and within the filter were also monitored, using Odyssey
297 capacitance probes. An Odyssey rain-gauge monitored rainfall using a 0.2 mm tipping
298 bucket. The basin was monitored from July 2013 to December 2016. Flow rate, water level
299 and rainfall were recorded at a 6 minutes timestep. In total, 22 rainfall events were selected
300 over the period to be used for the calibration (2 events) and validation (20 events) of the
301 model, ranging from 1 mm to 46 mm, with a median rainfall total of 7.7 mm.

302

303 2.2.3. Calibration and performance indicators

304 The objective of the model was to replicate the measured outflows, since this is the variable
 305 of most interest for stormwater managers. The goodness of fit between observed and
 306 simulated outflows was assessed by calculating the Nash Sutcliffe Efficiency (NSE; Eq. 9,
 307 (Nash and Sutcliffe, 1970)).

308
$$NSE = 1 - \frac{\sum_{i=1}^N (X_i^{obs} - X_i^{sim})^2}{\sum_{i=1}^N (X_i^{obs} - \overline{X_i^{obs}})^2} \text{ (Eq. 9)}$$

309 With X_i^{obs} the observed outflow value, $\overline{X_i^{obs}}$ the mean of observed value, X_i^{sim} the
 310 simulated value, N the number of timesteps per event.

311 For calibration, the model was run for thousands of combinations of parameters K_s and C_{out}
 312 (varied across their physically plausible range: K_s from 10^{-6} to 0.1 m/s, C_{out} between 0 and
 313 0.1) for the 2 rainfall events selected for calibration, with respective rainfall totals of 2 mm
 314 of rainfall, and 15 mm of rainfall, to cover the range of observed rainfall events. Parameters
 315 were adjusted to predict outflows, but the evolution of water levels was also checked to
 316 assess how well the model reflected the hydraulic gradient dynamics in the filter. Calibrated
 317 parameters K_s and C_{out} were obtained by maximizing the average of NSE_Q for flows for both
 318 events.

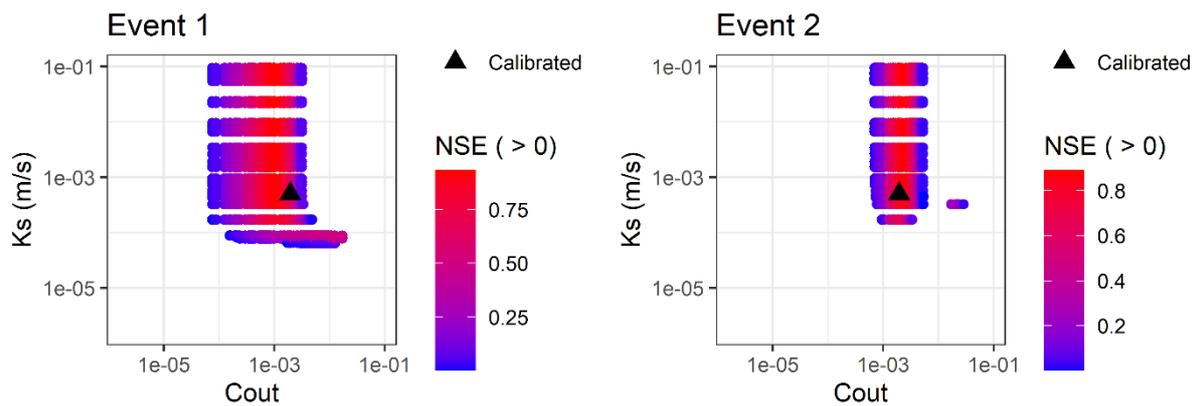
319 *Table 1: numerical values of parameters used in the model (bold values refer to the*
 320 *calibrated parameters).*

Parameters	Value
Filter depth (m)	0.8
Area of the ponding zone (m ²)	900
Area of the filter (m ²)	1800
Filter porosity	0.4
Wilting point θ_w	0.1
Field capacity θ_{fc}	0.2
Surrounding soil hydraulic conductivity (m/s)	$2.8 \cdot 10^{-7}$
Shape parameter m	0.5
Tortuosity τ	0.5
Saturated filter media hydraulic conductivity K_s (m/s)	$5 \cdot 10^{-4}$

Orifice coefficient C_{out}

$2 \cdot 10^{-3}$

321

322 For both calibration events, the saturated hydraulic conductivity of the filter K_s had less323 impact than the orifice coefficient parameter C_{out} . Nash Sutcliffe coefficients of efficiency324 were positive only for a certain range of tested values (Figure 3). The parameter K_s reached a325 threshold around $3 \cdot 10^{-4} \text{ m s}^{-1}$, from which it had very little impact on the performance of the326 model, and was fixed to $5 \cdot 10^{-4} \text{ m s}^{-1}$. The parameter C_{out} , reached 'optimum' values 1.2×10^{-3} 327 for the first calibration event and 2.5×10^{-3} for the second calibration event (Figure 3).328 Average value with $C_{out} = 2 \times 10^{-3}$ as an average of both previous C_{out} values was taken as the329 final calibrated value for C_{out} (Table 1).

330

331 *Figure 3: Evolution of the Nash Sutcliffe Efficiency between observed and simulated outflows*
332 *for the two calibration events.*

333

334 The model was then tested and validated with these parameters against 20 monitored

335 rainfall events, with two additional indicators calculated (Ahmadisharaf et al., 2019; Moriasi

336 et al., 2015): percent bias (PBIAS; Eq 10) and the root mean square error (RMSE, Eq. 11), in

337 order to validate the performance of the model.

338

$$PBIAS = \frac{\sum_{i=1}^N (X_i^{sim} - X_i^{obs})}{\sum_{i=1}^N X_i^{obs}} \text{ (Eq. 10)} \quad RMSE = \sqrt{\frac{\sum_{i=1}^N (X_i^{obs} - X_i^{sim})^2}{N}} \text{ (Eq. 11)}$$

339

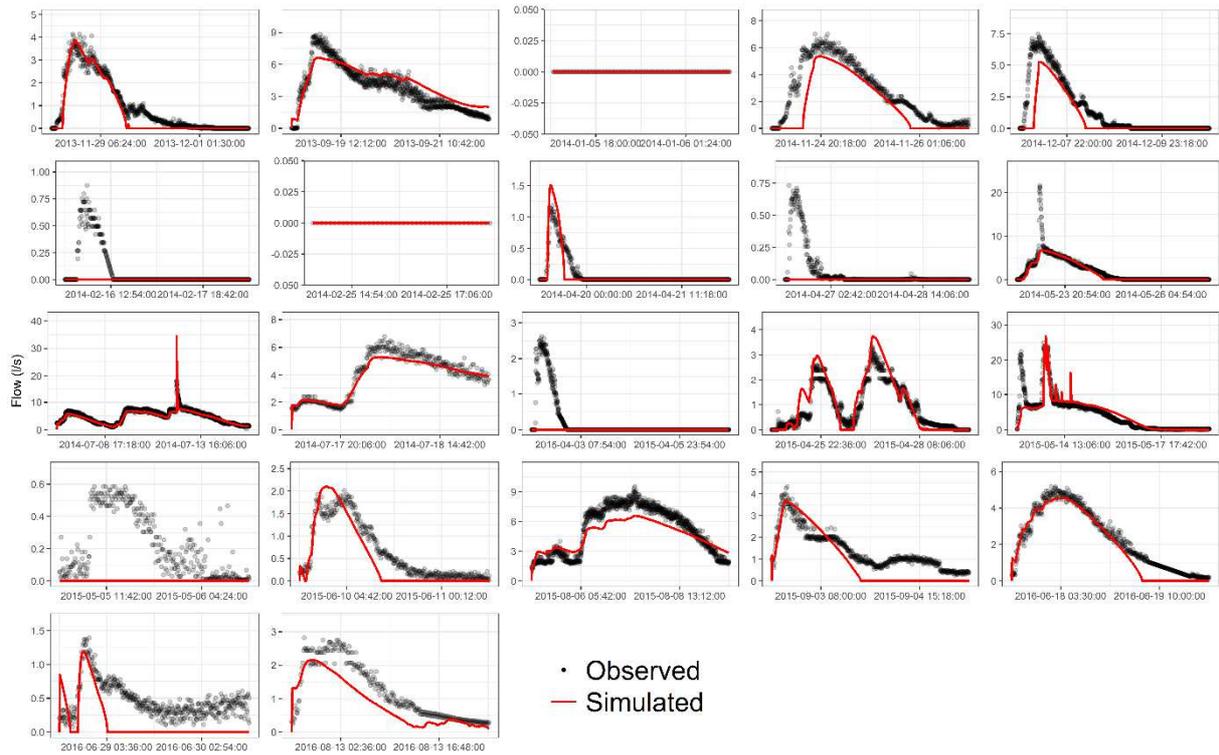
340 With X_i^{obs} the observed outflow value, $\overline{X_i^{obs}}$ the mean of observed value, X_i^{sim} the
341 simulated value, N the number of timesteps per event.

342 **3. Results and Discussion**

343 *Validation over 20 rainfall events*

344 The performance of the model tested over 20 rainfall events (excluding the two calibration
345 events) was satisfying (Figures 4 and 5), with a mean NSE of 0.53, a median NSE of 0.75 and a
346 median RMSE of 0.48 l/s. The model tended to underestimate fluxes, with a median PBIAS of
347 - 22% (Figure 5). Overall, the proposed model was able to well replicate outflows of the
348 basin for most rainfall events (Moriassi et al., 2015). However, the model was not able to
349 replicate water level dynamics in the filter (Mean and median NSE < 0). The water level
350 dynamics in the filter were not broadly well simulated (Figure 6). To better capture observed
351 water levels, additional soil hydrodynamic parameters would likely be required, allowing a
352 better simulation of the complexity of infiltration behavior (e.g., capillarity effects,
353 relationship between water content and hydraulic head, potential preferential flows or air
354 entrapment, etc.), but such information is not always easily available to end-users (Fournel
355 et al., 2013). The approach presented is a compromise between model parsimony and
356 performance, between being able to replicate observed water levels (arguably less
357 important than replicating observed outflows) and further complicating the model and its
358 calibration in practice. Flow data is indeed of the most interest in terms of impacts on water
359 quality and flow regimes of receiving waters (DeBusk et al., 2011). Poor replication of water
360 levels within the filter media possibly indicated oversimplification of geometry of the basin
361 and water infiltration, along with redistribution within the filter.

362

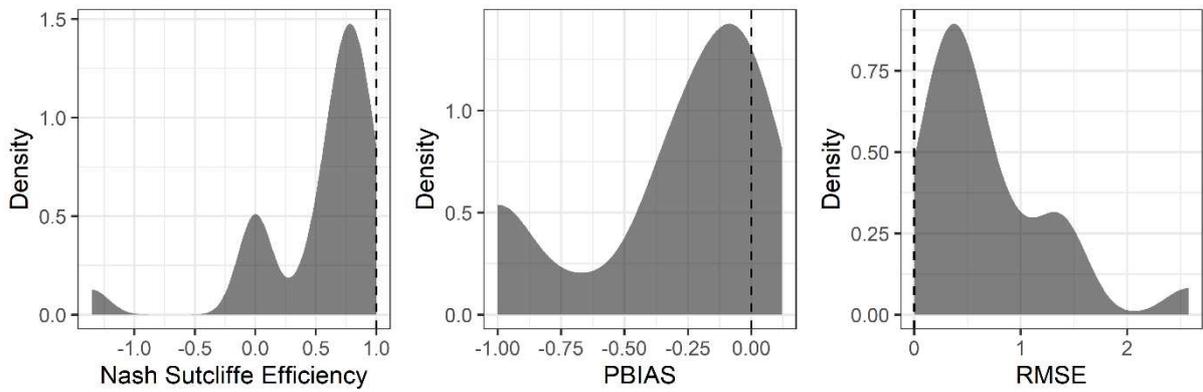


363

364 *Figure 4: Observed outflow hydrographs (black line with points = measured; red line =*
 365 *simulated with the proposed model)*

366

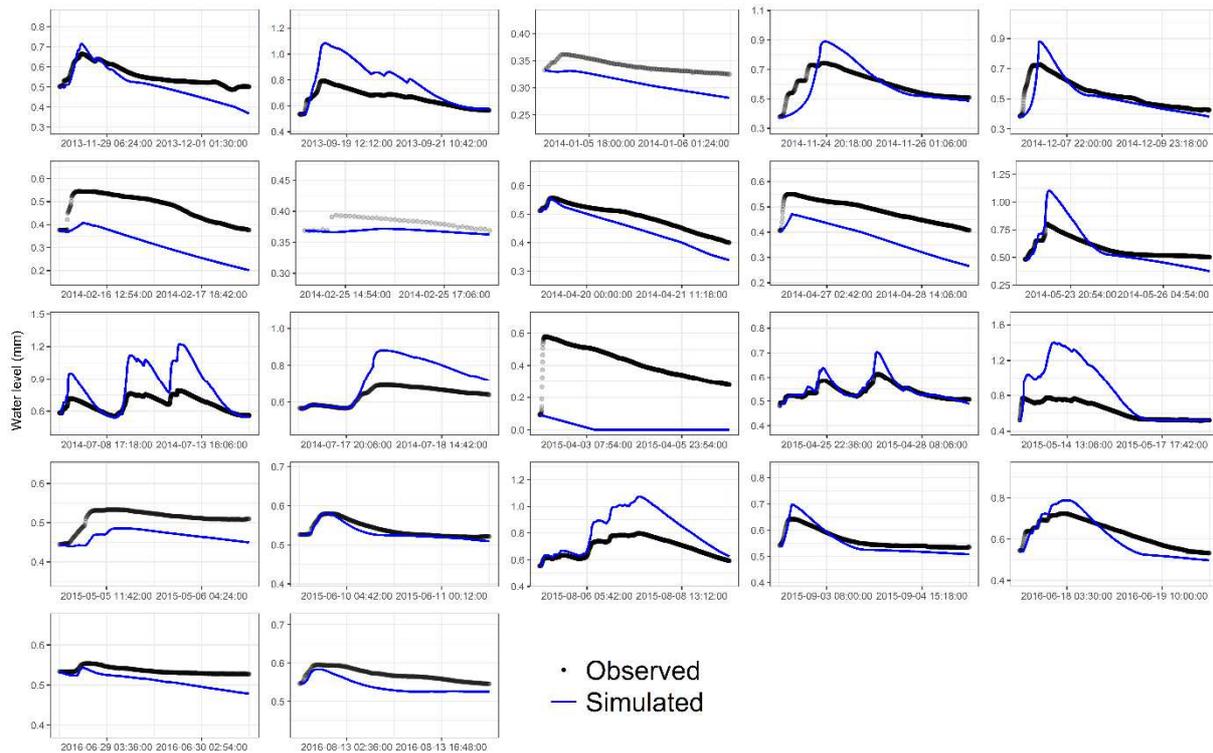
367



368

369 *Figure 5: Distribution of the Nash Sutcliffe efficiencies, PBIAS and RMSE for all the rainfall*
 370 *events.*

371



372

373 *Figure 6: Observed versus modelled water levels in the filter (black line with points =*
 374 *measured; blue line = simulated with the proposed model)*

375

376 *Discussion of the values of calibrated parameters*

377 The calibrated value of K_s ($5 \times 10^{-4} \text{ m s}^{-1}$) was one order of magnitude higher than expected,
 378 the design value of the sandy layers of the basin being $6.4 \times 10^{-5} \text{ m s}^{-1}$ (i.e., 230 mm. h^{-1}). This
 379 high value of the saturated hydraulic conductivity compares to typical values for sandy or
 380 gravels lithofacies (Goutaland et al., 2013). This might be due to the fact that in reality, the
 381 filter is fully vegetated with mature plants and developed root systems. The role of
 382 vegetation in increasing the hydraulic conductivity of bioretention systems is well
 383 documented and understood (Di Prima et al., 2020; Le Coustumer et al., 2009; Virahsawmy
 384 et al., 2013). The root systems, combined with bioturbation (animal and insects burrows)
 385 and even potential constructed shortcuts (the monitoring bores), can act as preferential
 386 (macropores) flow paths for water, increasing the effective hydraulic conductivity of the

387 filter. In this context, K_s represents the bulk saturated hydraulic conductivity, encompassing
388 the soil matrix and the effect of macropores (Lassabatere et al., 2019).

389

390 The calibrated orifice coefficient C_{out} (2×10^{-3}) was within the order of magnitude of what
391 could have been expected, usually found in the literature for perforated PVC pipes, though
392 this value would be hard to estimate in reality. Perforated pipes have holes with a specific
393 area around $2100 \text{ mm}^2/\text{m}$ (Department of Planning and Local Government of South
394 Australia, 2010), which, for a 100 m long pipe, with a clogging factor of 0.5 and a discharge
395 coefficient of 0.61, would result in $C_{out} = 0.064$. In reality, the contraction coefficient of a tiny
396 slot in a PVC is not well known, and might be lower than expected (corresponding to more
397 head loss resulting from more turbulence). In addition the actual state of clogging of the PVC
398 pipe was not known, particularly given the potential for plant roots to have penetrated the
399 orifices. The uncertainty around the design value for C_{out} is therefore not negligible, but the
400 calibrated value seemed in line with the site features.

401

402 *Description of processes at the scale of rainfall events.*

403 In the previous paragraphs, the full capability of the model to simulate observations was
404 assessed. Modeled data analysis can be used to understand processes at the scale of rainfall
405 events. At the start of every event, when the volume of water entering the surface storage
406 was low, all the inflow volume could enter the filter media, with an infiltration rate
407 controlled by Eq. 5c. In other words, the limiting factor for water infiltration was the amount
408 of water available at surface that was not enough to supply the quasi-infinite water fluxes
409 predicted by Darcy's equation. Infinite water fluxes in relation with infinite hydraulic
410 gradients (difference final minus initial water pressure heads spanned over small depths at

411 short times) are typical of infiltration rates into soils without additional restrictions
412 (Lassabatere et al., 2009). Eq. 5c was then lower than the potential flux computed by Eq. 5a
413 (Darcy's law) and governed the quantity of infiltrated water.

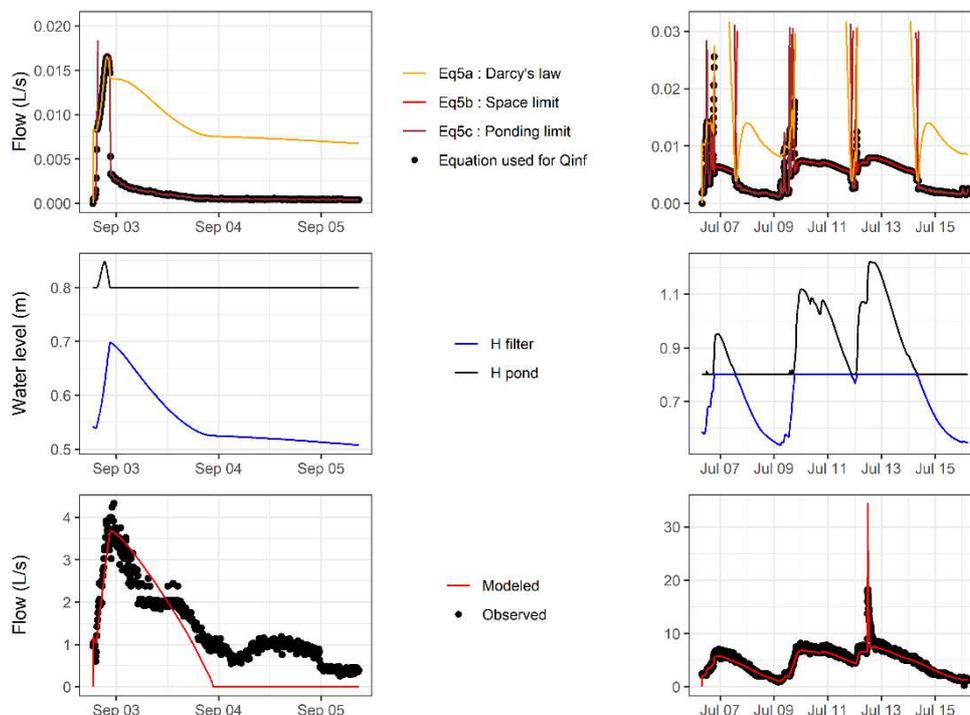
414

415 Afterwards, as more water entered the filter profile, such a gradient diminished and the
416 related amount of water to be infiltrated at surface decreased. The infiltration was then
417 controlled by Darcy's law and the unsaturated hydraulic conductivity of the filter. In other
418 words, not all the volume of water available at surface could be infiltrated, and any new
419 volume of entering water might add to the remaining volume of water. As a result, the water
420 began to pond at the surface, making the water levels rise. Meanwhile, the infiltrated water
421 increased the water level in the filter up to the level required for the onset of the underdrain
422 flow (Figure 7, left panels). Even with underdrain outflow, the water level in the filter was
423 not necessarily constant, but could continue to increase right up to the top of the filter
424 surface (Figure 7). In this case, the infiltrating water flux exceeded the sum of the outflow
425 rate, evapotranspiration and exfiltration to subsoils. As time passed and the rainfall events
426 ended, the inflow fluxes began to decrease, stopped in most cases, and became lower than
427 the infiltrating fluxes, thus limiting the amount of water available at the surface for
428 infiltration. Eq. 5c became again the limiting factor for infiltration into the filter. Meanwhile,
429 the water level decreased at surface (see the tail of Figure 7, left and right panels).

430

431 For some events (Figure 7, right panels), the basin filled up, with water levels getting close to
432 the surface. Consequently, the amount of water to be infiltrated was then truncated to the
433 space available in the filter. The equation Eq 5b became the minimum among equations (5),
434 thus driving the infiltrated volume. In the case of large rainfall events, the water levels in the

435 filter eventually reached the surface, increasing water ponding, sometimes up to the
 436 overflow level. The system was then fully saturated. Afterwards, following the decrease in
 437 entering fluxes, the volume of water in the filter decreased by evapotranspiration,
 438 exfiltration and underdrain flow, allowing the water from the surface to infiltrate again. With
 439 the decrease of water levels in the filter, the space available in the filter was no longer
 440 limiting. The infiltration shifted back to Darcy's law. Figure 7 also illustrates the fact that the
 441 shape of modelled outflow is the same as the shape of the sum of the water levels in the
 442 filter media and at the surface. The underdrain outflow rate (Eq 8) is controlled by the orifice
 443 coefficient C_{out} , which proved to drive most of the behaviour of the model of the
 444 bioretention basin. If C_{out} was too high, the orifice would limit the water level in the filter,
 445 preventing it from reaching the surface, which was not consistent with some observations.
 446 Conversely, too low values of C_{out} would lead to full saturation of the bio-retention system
 447 even for small rainfall amounts.



449 *Figure 7: For two rainfall events (right/left): Top: Infiltration fluxes from the surface store to*
450 *the filter media. Middle: Water levels at the surface (black line) and in the filter media (blue*
451 *line). Bottom: Modelled and observed outflows*
452

453 *Genericity of the proposed model, limitations and future research*

454 The proposed model may be applied to any bioretention system. Indeed, it requires the
455 calibration of two key parameters to fix *a priori*: the saturated hydraulic conductivity of the
456 filter – usually obtainable - and the coefficient C_{out} that characterizes the underdrain – much
457 harder to estimate. All the other parameters can be easily described from readily-available
458 design information (see table 1). Most of them are standard design features of the
459 bioretention system (area, thickness, etc.). The filter porosity, wilting point, and field
460 capacity can be easily fixed as a function of the type of material constituting the filter, based
461 on widely known properties. We advise keeping the specific parameters m and τ to the
462 values of 0.5, which suits an extensive range of coarse materials. The low number of
463 parameters to calibrate reduces concerns regarding parameter equifinality and non-
464 uniqueness (Pollacco, J.A.P. et al., 2013; Pollacco et al., 2008). These parameters should be
465 estimated using a few rainfall events. The proposed model can be considered as a sound
466 basis for further developments. First of all, the model focuses on the simulation of the piped
467 outflow fluxes including the overflow and the underdrain outflow. However, modelling of
468 water levels in the filter must be improved. The proposed model was not able to deal with
469 empty initial conditions. For events with very little water in the filter initially, the initial
470 effective saturation was set to the wilting point (Eq 2a), but such values were too low for the
471 infiltration to 'start' (Eq 4 resulting in very low unsaturated hydraulic conductivity). This
472 resulted in water staying in the ponding zone and not entering into the filter, and therefore
473 there was no outflow modeled at all (see event of April 2015, 3rd row and 3rd column on
474 Figures 4 and 6). Better accounting for initial conditions is necessary for future versions.

475

476 To alleviate such problems, we suggest working on the implementation the concomitant fit
477 of water fluxes and water levels to estimate the model input parameters. Several weighing
478 procedures could be tested to see the improvement on fits and estimates (Pollacco, J.A. et
479 al., 2013). We also suggest working on the improvement of approximations considered for
480 the modelling of complex processes. First of all, capillarity effects were simplified and the
481 water retention curves were approximated to stepwise functions. Following such
482 approximation, a bulk saturation degree was uniformized and evenly distributed along the
483 whole filter profile. Then, the bulk hydraulic conductivity was computed from the average
484 saturation degree using Mualem capillary models. Meanwhile, the hydraulic gradient was
485 discretised at the scale of the filter, by dividing the difference in water pressure head by the
486 filter depth. This process of “averaging” at the scale of the filter, considered as one “box”, is
487 far from the precise description of the downward movement of wetting fronts and
488 infiltration processes. The loss of precision on water level due to the gain in simplicity should
489 be investigated in more depth, using for instance numerically generated data. In addition,
490 the model is based on the single permeability approach, whereas preferential flow may
491 occur in reality (due to the presence of macropores). Dual porosity or dual permeability
492 systems could thus be considered (Gerke and Van Genuchten, 1993), as is done for models
493 of water infiltration into soils (Lassabatere et al., 2014). The implementation of dual
494 permeability approaches for the modelling of preferential flow, as potentially induced by
495 plant root systems, will be the subject of further studies (Asry et al., 2021).

496

497

498 **4. Conclusions**

499 A hydrologic model of a bioretention basin was built, based on equations representing all
500 the components of the hydrological balance (water infiltration, evapotranspiration,
501 underdrain outflow, overflow, exfiltration) in the different components of the studied basin
502 (surface basin, filter). The main conclusions and observations, after a thorough field
503 validation of the model, are as follows:

- 504 • It is possible to replicate outflows of a bioretention basin with a relatively simple
505 model provided it is calibrated. Only 2 rainfall events were used for the calibration,
506 making it suitable for a wide range of applications where resources for calibration are
507 limited.
- 508 • The model performed well in reproducing the overall hydrological behaviours of the
509 basin with respects to water outflows, and in particular the main features of
510 contrasting scenarios.
- 511 • Further improved performance (such as improved replication of water level
512 dynamics) would require additional parameters to describe the physical functioning
513 of the basin, in terms of water transfers between the surface, the filter and the
514 underdrain, taking into account the whole complexity of physical processes
515 governing water infiltration into the filter. However, these parameters will degrade
516 the model parsimony and require additional calibration effort.
- 517 • This proposed model could be readily incorporated into an LID toolbox of catchment-
518 scale hydrological software, which are becoming increasingly used around the world.
- 519 • The model performance is particularly sensitive to one parameter, the orifice
520 coefficient of the underdrain perforated PVC pipe, which is very hard to physically

521 estimate. Further research should focus on appropriate methods for characterizing
522 this coefficient.

523 With the proposed approach, we provided the first step towards the design of a user-
524 friendly model for the operation of low-impact drainage systems, leading to manage
525 stormwater in urban areas better. The proposed model was validated against experimental
526 data and showed promise for further development and validation on different types of
527 stormwater control measures.

528

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545 **References**

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