

# Assessing the impact of spatial allocation of bioretention cells on shallow groundwater – an integrated surface-subsurface catchment-scale analysis with SWMM-MODFLOW

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9 **Abstract:** Well-designed and implemented green infrastructure (GI) can help to recover the natural  
10 hydrologic regimes of urban areas. Large-scale GI planning requires understanding the impact of GI spatial  
11 allocation on surface-subsurface hydrologic dynamics. This study develops a coupled surface-subsurface  
12 hydrological model (SWMM-MODFLOW) that simulates fine-temporal-scale two-way interactions  
13 between GI and groundwater at a catchment scale. The model was calibrated and validated using monitoring  
14 data from an urban catchment within Kitsap County, WA, US. Based on the validated model, a series of  
15 hypothetical simulations were then performed to evaluate how the spatial allocation of GI, in particular  
16 bioretention cells, influences and correlates with surface runoff and groundwater table dynamics. The spatial  
17 allocation was represented by the implementation ratio (i.e., area), the aggregation level (i.e., density), and  
18 the location of bioretention cells. The dynamics were quantified by peak and volume reductions of surface  
19 runoff, as well as groundwater table rise and the standard deviation of groundwater levels. The  
20 implementation ratio of bioretention cells was found to be the main spatial feature that governed both surface

21 runoff and groundwater table dynamics. With the implementation of more bioretention cells, greater amounts  
22 of runoff could be controlled and the groundwater table rose, but the spatial uniformity of regional  
23 groundwater levels (i.e., the standard deviation of groundwater levels) was not significantly affected.  
24 Bioretention cells should therefore be allocated in a distributed pattern when groundwater table depth is  
25 relatively uniform. Allocating bioretention cells in upstream areas can generally raise the groundwater levels  
26 downstream, but their exact locations must still be determined based on the geophysical conditions and  
27 spatial variations within the catchment. Bioretention cells with greater surface runoff control efficiencies  
28 lead to higher groundwater table rises, which highlights the importance of considering tradeoffs between  
29 surface runoff control and groundwater protection in GI planning.

30 **Keywords:** low impact development; bioretention cell; stormwater management; integrated modeling;  
31 groundwater modeling; urban planning

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### 33 1. Introduction

34 Excessive urbanization has significantly deteriorated natural hydrological, ecological, and biological  
35 regimes. There is now a general consensus that more sustainable and environmentally friendly development  
36 approaches are needed (Song, 2005). Green infrastructure (GI) has been proposed as an approach for this  
37 conceptual revolution (Brown et al., 2009). However, the definition of GI can vary. For fields concerned  
38 with hydrology and stormwater management, GI is analogous to concepts such as low impact development  
39 (LID), sustainable urban drainage systems (SUDS), and water sensitive urban design (WSUD), which  
40 represent a group of semi-natural spatially distributed stormwater management practices (Potter, 2006;  
41 Young et al., 2014; Fletcher et al., 2015). Compared with traditional drainage systems, these possess more

42 diverse functionalities, which include collecting, storing, and infiltrating rainfall runoff, and recovering  
43 natural hydrological cycles (Chui et al., 2016). Representative practices include bioretention cells, porous  
44 pavements, green roofs, etc. Alternatively, for fields such as landscape design and urban planning, GI can  
45 include forests or other green spaces that provide other environmental benefits such as urban heat island  
46 mitigation and biodiversity improvement (EC, 2013; Zhang and Chui, 2019). GI as referred to in this study  
47 follows the first definition, focusing on hydrology and stormwater management.

48 Among the benefits that GI can provide, such as reduction of peak runoff and control of non-point  
49 source pollution, groundwater recharge is one benefit that attracts relatively little attention (Jefferson et al.,  
50 2017; Sohn et al., 2019). One reason for this may be that recharging groundwater using GI comes with many  
51 challenges, which are particularly prominent in shallow groundwater areas. For example, a groundwater  
52 mound can form when the groundwater recharge rate exceeds the dissipation rate. This may slow down or  
53 inhibit surface infiltration, and increases the risk of groundwater contamination due to a shorter traveling  
54 distance and more carried pollutants (Fischer et al., 2003; Datry et al., 2004; Göbel et al., 2004; Endreny and  
55 Collins, 2009; Machusick et al., 2011; Stewart et al., 2017; Zhang and Chui, 2017; Zhang and Chui, 2018a).  
56 However, recharging groundwater using GI can increase the baseflow, recover the hydrological cycle, and  
57 help maintain urban water supplies (Newcomer et al., 2014; Bhaskar et al., 2016, 2018; Bradshaw and Luthy,  
58 2018). It should therefore be promoted in the appropriate conditions, such as in locations with suitable  
59 subsurface soil properties and a relatively deep groundwater table (Trinh and Chui, 2013; Chui and Trinh,  
60 2016).

61 For the reasons aforementioned, the objectives and constraints of groundwater recharge should be  
62 thoroughly considered in GI planning. However, maximizing the control of surface runoff often remains the

63 dominant objective in GI implementation. As reviewed by Zhang and Chui (2018b), many studies considered  
64 the peak and volume control of surface runoff (Perez-Pedini et al., 2005; Damodaram and Zechman, 2013;  
65 Sebti et al., 2016; Giacomoni and Joseph, 2017; Lim and Welty, 2017; Voter and Loheide, 2018). Other  
66 studies considered pollution mitigation of surface runoff (Maringanti et al., 2009; Rodriguez et al., 2011;  
67 Chiang et al., 2014; Chen et al., 2015, 2016), and some examined the two aspects together (Lee et al., 2012;  
68 Liu et al., 2016a, 2016b; Mao et al., 2017; Xu et al., 2018). For the relationship between GI and groundwater,  
69 some studies assessed the response of shallow groundwater to GI (Endreny and Collins, 2009; Trinh and  
70 Chui, 2013, Chui and Trinh, 2016; Zheng et al., 2018), while others proposed recommendations about  
71 suitable distances between GI and the groundwater table (Locatelli et al., 2015; Zhang and Chui, 2017;  
72 Muñoz-Carpena et al., 2018; Lauvernet and Muñoz-Carpena, 2018). However, the impact of GI spatial  
73 allocations on shallow groundwater table dynamics remains to be evaluated.

74 The spatial allocation of GI is hypothesized to affect the groundwater table dynamics in a number of  
75 aspects. Based on the study of Zhang and Chui (2018b), the spatial allocation of GI can be mainly represented  
76 by the implementation ratio (i.e., area), aggregation level (i.e., density), and location. First, the  
77 implementation ratio of GI is a major factor because it determines the amount of rainfall that can be infiltrated.  
78 With a higher implementation ratio, more water can be recharged, and the groundwater table should rise  
79 higher. Second, the aggregation level of GI is also influential, because more-aggregated GI practices can  
80 cause local water infiltration and result in groundwater mounds as reported by Endreny and Collins (2009).  
81 Third, the location of GI also matters, as the land use and geologic conditions (e.g., the hydraulic properties  
82 of in-situ soil, groundwater table depth) can be very different at different locations. Specifically, in areas of  
83 higher imperviousness, more permeable soils, and shallower groundwater tables, GI can affect the

84 groundwater table dynamics more dramatically, due to greater surface runoff and higher infiltration and  
85 recharge rates. The concept of variable source area explains the impacts of these factors (Miles and Band,  
86 2015; Lim, 2016). Additionally, the spatial allocation of GI can be determined, based only on land use and  
87 geologic factors, by using spatial analysis tools without hydrological analysis (Martin-Mikle et al., 2015;  
88 Johnson and Sample, 2017).

89 Although there are many different numerical models that can simulate the hydrological processes of GI,  
90 they all have limitations in simulating GI in shallow groundwater environments. As reviewed by Zhang et  
91 al. (2018), variably saturated porous media software, e.g. COMSOL Multiphysics, VS2D, Hydrus 1D/2D/3D,  
92 have been used in some cases (He and Davis, 2010; Stewart et al., 2017; Zhang and Chui, 2017). However,  
93 they generally cannot handle, or are not suitable for, catchment-scale studies because they simplify or cannot  
94 simulate rainfall-runoff generation and surface runoff routing. Alternatively, some surface-subsurface  
95 hydrological models (e.g., MODHMS, MIKE-SHE, and VELMA) can better simulate rainfall-runoff  
96 processes and are more widely used at the catchment scale (Barron et al., 2013; Trinh and Chui, 2013;  
97 Locatelli et al., 2017; Hoghooghi et al., 2018). However, they mostly operate at relatively coarse temporal  
98 and spatial resolutions, which are beyond the normal scales of individual GI practices. Thus, in all current  
99 models certain time- and space-sensitive hydrological processes important to GI are overly simplified. Many  
100 of these tools are also commercial or non-open source software, which makes them harder to improve or  
101 integrate with other tools for data analysis and optimization. Importantly, neither type of model can simulate  
102 urban hydraulics, such as storm sewer systems, which limits their usage in urban areas where GI may have  
103 the greatest impact.

104 As an urban hydrologic-hydraulic model, SWMM has been widely adopted to simulate GI, including

105 to assess the hydrological and water quality treatment performance of GI (Qin et al., 2013; Palla and Gnecco,  
106 2015; Chui et al., 2016; Jayasooriya et al., 2016; Avellaneda et al., 2017; Kong et al., 2017). It is also used  
107 to evaluate the optimal designs and allocations of GI (Elliott et al., 2009; Lucas and Sample, 2015;  
108 Giacomoni and Joseph, 2017; Macro et al., 2018; Yang and Chui, 2018a, 2018b; Zischg et al., 2018).  
109 However, SWMM is not as capable in simulating the subsurface hydrological performance of GI. First, it  
110 highly simplifies the simulation of unsaturated and saturated flows by assuming a linearized soil water  
111 retention curve. Second, it neglects the impact of groundwater on the hydrological processes of GI (e.g.,  
112 exfiltration, percolation, underdrain flow) (Lee et al., 2018; Zhang et al., 2018). To partially overcome these  
113 deficiencies, Zhang et al. (2018) improved SWMM by creating an interface to incorporate groundwater  
114 levels into the simulation of GI, and showed that the modified SWMM is appropriate for simulating the  
115 performance of GI in shallow groundwater environments. However, it cannot simulate groundwater  
116 dynamics and requires the direct input of groundwater levels, which greatly hinders its application.

117 This study integrates the modified SWMM, named SWMM-LID-GW, with MODFLOW, which is a  
118 finite-difference groundwater flow model developed by U.S. Geological Survey, to develop a loosely  
119 coupled surface-subsurface hydrological model, named SWMM-MODFLOW. It is loosely coupled because  
120 the two models were integrated through external file input and output without internal function calls. The  
121 coupling approach utilized in this study is similar to that of Zhang et al. (2018), however, the groundwater  
122 dynamics are simulated instead of being input, and two-way interactions between GI and groundwater are  
123 realized. The model was calibrated and validated using monitoring data from an urban catchment at  
124 Silverdale, WA, in the US. Then, using a bioretention cell (BC) that allows exfiltration as a representative  
125 GI, a series of hypothetical scenarios of different spatial allocation patterns of BCs was simulated, which

126 covered different implementation ratios, aggregation levels, and locations of BCs within the same catchment.  
127 The influence of the spatial allocation of BCs on surface runoff and groundwater table dynamics was also  
128 evaluated. Finally, the correlations between surface runoff and groundwater table dynamics were examined.  
129 This study focused on groundwater, rather than surface runoff, dynamics because they are less studied and  
130 understood.

131

## 132 **2. Methodology**

### 133 **2.1 Modeling framework of SWMM-MODFLOW**

134 A two-way coupled surface-subsurface hydrological model, SWMM-MODFLOW, was developed and  
135 utilized. It is a loosely coupled model linking SWMM and MODFLOW, and its structure is shown in Fig. 1.  
136 Retaining the main structures of SWMM and MODFLOW, the coupling was performed through file input  
137 and output without internal function calls between the source codes of the two models. More specifically,  
138 the surface infiltration rate in non-GI-pervious areas, or the exfiltration rate at the bottom of the GI, was sent  
139 from SWMM to MODFLOW, while groundwater table depth was sent from MODFLOW to SWMM (Fig.  
140 1). Based on the groundwater table depth obtained from MODFLOW, the hydrological processes of GI  
141 including underdrain flow, exfiltration rate, and surface runoff, were calculated using the equations of  
142 SWMM-LID-GW developed by Zhang et al. (2018) (Eq. 1-2). Furthermore, MODFLOW can also simulate  
143 groundwater table dynamics after receiving the infiltration and exfiltration rates from SWMM. The  
144 governing equations of underdrain flow of GI, exfiltration rate of GI, and groundwater flow in MODFLOW  
145 are shown by Eq. 1, 2 and 3 below respectively:

146 
$$f_{drain} = \begin{cases} A \times (h_{WS} - h_{offset})^B & \text{(if } h_{WS} \geq h_{GW} \text{)} \\ A \times (h_{GW} - h_{offset})^B & \text{(if } h_{WS} < h_{GW} \text{)} \end{cases} \quad (\text{Eq. 1})$$

147 where  $f_{drain}$  is the rate of underdrain flow;  $A$  and  $B$  are the two coefficients of underdrain, which depend on  
 148 the size and the density of holes on the underdrain, respectively;  $h_{offset}$  is the distance between the  
 149 underdrain and the bottom of the GI;  $h_{WS}$  is the depth of water storage within the GI; and  $h_{GW}$  is the distance  
 150 between the groundwater table and the bottom of the GI.

151 
$$f_{exfil} = \frac{\theta_s - \theta}{\theta_s - \theta_i} \times K_s \quad (\text{Eq. 2})$$

152 where  $f_{exfil}$  is the exfiltration rate;  $K_s$  is the saturated hydraulic conductivity of the in-situ soils;  $\theta_s$  and  $\theta_i$   
 153 are the saturated and initial moisture contents, respectively, of the in-situ soils; and  $\theta$  is the current moisture  
 154 content of the in-situ soil near the bottom of the GI, which depends on the groundwater table depth. The  
 155 exfiltration rate varies with the groundwater table depth and the soil moisture of in-situ soils. This rate  
 156 becomes equal to  $K_s$  when the soil moisture of in-situ soils is equal to  $\theta_i$ , and the rate reduces to zero when  
 157 the groundwater table rises to, or above, the bottom of the GI. It should be noted that the initial moisture  
 158 content of the in-situ soils ( $\theta_i$ ) was updated for every time step, and was based on the groundwater table  
 159 depth of nearby GI. Some of the variables mentioned above are illustrated in Fig. 2.

160 
$$\frac{\partial}{\partial x} (K_x \frac{\partial h}{\partial x}) + \frac{\partial}{\partial y} (K_y \frac{\partial h}{\partial y}) + \frac{\partial}{\partial z} (K_z \frac{\partial h}{\partial z}) = S_s \frac{\partial h}{\partial t} \quad (\text{Eq. 3})$$

161 where  $K_x$ ,  $K_y$ , and  $K_z$  represent the hydraulic conductivity in the  $x$ ,  $y$ , and  $z$  directions;  $S_s$  represents the  
 162 specific storage; and  $h$  represents the average groundwater head of grids beneath the GI, which was used to  
 163 calculate the soil moisture at the bottom of the GI (i.e.,  $\theta$  in Eq. 2) through the Van Genuchten equation.

164 Overall, the coupled model can characterize the variations of hydrological processes of GI, with respect  
 165 to groundwater table depth. When the groundwater table fluctuates, the underdrain flow and exfiltration rates

166 can vary, as characterized by the equations above. As a result, the percolation rate from soil layer to storage  
167 layer, the surface infiltration rate, and the rate of surface runoff may also vary according to the water balance  
168 inside the different layers of GI. For example, when the groundwater table is shallower than the bottom of  
169 both the GI and the underdrain pipe, the exfiltration stops and the underdrain flow is governed by the  
170 groundwater table instead of the percolation rate. Thus, the maximum percolation and surface infiltration  
171 rates should be equal to the rate of underdrain flow. More details about these features can be found in Zhang  
172 *et al.* (2018).

173 The data exchange was governed by a MATLAB controller. The detailed mechanisms of the MATLAB  
174 controller and the data exchange are also shown in Fig. 1. The controller realized temporal synchronization  
175 between the two models by using the “hot-start” functions, which allowed the two models to pause and re-  
176 start from a previous time step when necessary. More specifically, one simulation was segmented into  
177 multiple time steps. After the completion of each time step, one model was paused with the results of this  
178 time step stored into external hot-start files, and then sent to the controller for processing. The other model  
179 was then activated by the controller after receiving the processed results (Fig. 1). The hot-start function in  
180 SWMM was already improved by Zhang *et al.* (2018) to support the storage and extraction of GI simulation  
181 results including soil moisture of the soil zone, water depth at the surface, and water depth inside the storage  
182 layer, into the external hot-start files (Fig. 1). However, there is no similar built-in function in the current  
183 version of MODFLOW. Thus, a hot-start function was developed in MODFLOW by transferring and  
184 modifying the source code from GSFLOW, another surface-subsurface hydrological model coupled by the  
185 Precipitation-Runoff Modeling System (PRMS) and MODFLOW (Regan *et al.*, 2015). With similar  
186 functionalities to those of SWMM, the hot-start function of MODFLOW can store and extract groundwater

187 heads and percolation rates in different layers of grids at the end and start of each time step. Details about  
188 the hot-start functions in SWMM and MODFLOW can be found in Zhang et al. (2018) and Regan et al.  
189 (2015) respectively.

190 The controller performed the spatial mapping between two models by processing the results from each  
191 model into organized and transferable formats. This is necessary because the spatial representation  
192 approaches of the two models are completely different. SWMM is a sub-catchment-based spatially lumped  
193 model, but MODFLOW is a grid-based finite-difference model, as shown in Fig. 3. The controller extracted  
194 the infiltration rate of pervious areas, or the exfiltration rate of GI, from the output files of SWMM and  
195 discretized them into matrixes, which were then updated into the input files of MODFLOW (Fig. 1 and 3).  
196 Simultaneously, the controller extracted matrixes of groundwater heads from the output files of MODFLOW,  
197 modified these into groundwater table depths, lumped them into sub-catchment-based values, and then  
198 updated these values into the input files of SWMM (Fig. 1 and 3). Although the locations of GI within sub-  
199 catchments cannot be specified in SWMM, they can be accurately located in MODFLOW (yellow rectangles  
200 in Fig. 3) with three indicators: the index of sub-catchment; the index of GI within each sub-catchment; and  
201 the coordinates of grids of GI. This mapping process is schematically illustrated in Fig. 3.

202 **2.2 Study area and data**

203 An urban catchment in Silverdale, Kitsap County, WA, US was selected as the study area (Fig. 4). The  
204 study area is 197 ha in size with approximately 80% urbanization, and is located on the Kitsap Peninsula  
205 (Fig. 4b) lying at the northern tip of the Dyes Inlet, which is connected to the Puget Sound. The area is of  
206 equable oceanic climate with generally mild temperatures, and moderate to heavy precipitation (Sceva, 1957).  
207 It has warm dry summers and relatively mild winters. The precipitation averages 1103.6 mm/year with 161

208 precipitation days, and the reference evapotranspiration (ET) averaged 741.7 mm/year during 1991-2018.

209 The detailed properties of the sub-catchments can be found in Table 1.

210 The catchment is located at a Pleistocene depositional unit in Kitsap County. The major soil types of the  
211 area include, but are not limited to, bedrock, advanced outwash, gravels, lacustrine, peat, and till, based on  
212 local geologic surveys (Sceva, 1957) and the SSURGO soil database (NRCS and USDA, 2017). The northern  
213 and western parts of the catchment are mountainous with an average slope of 10–14%, so the highest  
214 locations were assigned as the domain boundaries in these two directions, which were assumed as no-flow  
215 boundaries in the groundwater model (the light gray boundary in Fig. 4c). The southwestern and eastern  
216 sides of the catchment lie in the Strawberry Creek (the blue boundary in Fig. 4c) and the Clear Creek (the  
217 green boundary in Fig. 4c), respectively. The southern boundary is connected to the Dyes Inlet (the yellow  
218 boundary in Fig. 4c). In addition, discrete groundwater level data within the catchment (black triangles in  
219 Fig. 4c) were retrieved from the Environmental Information Management System (EIM) of Washington State,  
220 and were used to estimate the initial groundwater levels of the catchment through extrapolation. The  
221 groundwater levels observed are within 30 m below the land surface, and were highest during the late spring  
222 months and lowest in the late fall and early winter months (Sceva, 1957).

223 One year of monitoring was performed by Kitsap County at an urban catchment near the Central Kitsap  
224 County Campus (CKCC), which is located at the central part of the catchment (Fig. 4c and 3d). The CKCC  
225 site is 2.63 ha in size, within which nine BCs and 10 parcels of porous pavements are implemented. The BCs  
226 are 35–146.8 m<sup>2</sup> in size, which allows a surface ponding depth of 100 mm, and consist of soil and storage  
227 layers of 400 mm and 380 mm in thickness, respectively. The soil layers were filled by an amended soil mix  
228 and the storage layers were filled by washed aggregated (AASHTO No. 57). The porous pavements are 238–

229 1710 m<sup>2</sup> in size, consisting of pavement and storage layers of 50 mm and 750 mm in thickness, respectively.

230 The pavement layer is made up of Eco-Priora concrete pavers and AASHTO No. 8 aggregate in the openings.

231 The storage layer is made up of an open-graded base and a subbase, which are filled by AASHTO No. 57

232 and No. 2 aggregates, respectively. These GI practices are connected to the storm sewer system via 150-mm

233 underdrains. The hydrologic properties of the different layers of both types of GI practices are shown in

234 Table 2, and their detailed designs can be found in Herrera (2013) and Zhang *et al.* (2018). Five datasets are

235 available for 1 year from October 1, 2011 to September 30, 2012. These include surface runoff from the

236 rooftop of the Haselwood Family YMCA building (0.46 ha) (*ROOF\_SR*), surface runoff from one impervious

237 area of 0.068 ha (*IP\_SR*), underdrain flow of one parcel of porous pavement (0.17 ha) (*PP\_UD*), the pipe

238 flow at the sewer outlet of the catchment (2.63 ha) (*OUTLET*), and the groundwater table depth at one

239 location within the site (*GW\_DEPTH*). All of the datasets were continuous, and were at a temporal resolution

240 of 5 min. The locations of the monitoring stations are shown in Fig. 4d, and more details about the monitoring

241 approaches and devices can be found in Zhang *et al.* (2018).

## 242 2.3 Model settings

### 243 2.3.1 SWMM

244 Given that SWMM is a spatially lumped model, the catchment was separated into 14 sub-catchments,

245 or hydrologic response units, in SWMM (Fig. 4c). The hydrologic response units were delineated based on

246 the topography and soil type using ArcGIS. Due to the relatively consistent geophysical and hydrological

247 characteristics within each unit, each sub-catchment was considered as homogeneous in its hydrologic

248 responses. The area and the imperviousness of the sub-catchments ranged from 7.67 ha to 24.23 ha, and from

249 47.49% to 100%, respectively (Table 1).

250 The Dynamic Wave model was used for flow routing in the storm sewers, and the Green-Ampt equation  
251 was used as the infiltration model, which allowed the consideration of surface ponding. This model may  
252 slightly overestimate the hydraulic conductivity (Triadis and Broadbridge, 2012), but it obtained similar  
253 results as that calculated by the Richards equation for GI practices (Dussaillant *et al.*, 2004). GI practices  
254 were placed within sub-catchments in a lumped manner instead of being independently represented. The  
255 detailed hydrologic properties of GI practices can be found in Table 2. After implementing GI practices into  
256 sub-catchments, the properties of the sub-catchments were modified, including the imperviousness, width,  
257 and percentage of impervious area treated by GI. The details of these modifications are elaborated in the  
258 following sections as necessary.

259 2.3.2 MODFLOW

260 The grid size in MODFLOW was set as 23 m × 23 m, considering the trade-offs between sub-catchment  
261 size and the normal size of GI, and between computation accuracy and cost. Based on the geologic conditions,  
262 the area was segmented into three subsurface layers, the thicknesses of which were 0–30 m, 0–15 m, and 0–  
263 15 m, respectively. The upper two layers were set as convertible (i.e., can switch between unconfined and  
264 confined) and the bottom layer was set as confined. The properties of the layers and the flow between layers  
265 and grids were simulated using the Layer Property Flow (LPF) package, which allowed the simulation of  
266 dewatered conditions.

267 The surface infiltration (retrieved from SWMM in each time step) was simulated as a specified flux into  
268 the subsurface layers using the Recharge (RCH) package. The ET was simulated using the EVT package,  
269 and the monthly averaged ET rate in the study area was used with an ET root depth of 0.5 m. The River  
270 (RIV) package was used to simulate the river boundaries (i.e., Clear Creek and Strawberry Creek), which

271 were represented as head-dependent flux. The river stages of these two rivers, retrieved from the Kitsap  
272 Public Utility District, were simply assigned as the heads of these two boundary conditions, assuming the  
273 rivers are connected to the unconfined aquifer underneath. This assumption is reasonable because the base  
274 flow of these two creeks is primarily from groundwater discharge during summer (Sebren, M.B., 2017). In  
275 addition, the General-Head Boundary (GHB) package was used to simulate the boundary of the sea (i.e.,  
276 Dyes Inlet), and the sea level, retrieved from the NOAA Tides and Currents database, was assigned as the  
277 head of the boundary condition.

278 In addition, it should be noted that the coupled SWMM-MODFLOW ran hourly, but SWMM and  
279 MODFLOW ran at a time step of 5 min. The Preconditioned Conjugate-Gradient (PCG) package was used to  
280 solve the finite difference equations in MODFLOW, with a maximum number of iterations of 150, a  
281 relaxation parameter of 0.97, and a maximum absolute change in head of 0.01 m.

282 **2.4 Model calibration and validation**

283 Although some types of information about the catchment, like the thickness of the aquifer and the soil  
284 type distribution, are available, the exact modeling parameter values may still be unknown, because some  
285 parameters are not directly observable. These include the drainage coefficient of underdrain, Manning's n of  
286 overland flow and conduit, and the depression storages of impervious and pervious areas. Other parameters  
287 may vary significantly in their ranges, such as the hydraulic conductivity, specific yield, and specific storage  
288 of soils. Thus, the parameters were calibrated first.

289 The model was calibrated and validated using the monitoring datasets at the CKCC site, including  
290 *ROOF\_SR*, *IP\_SR*, *PP\_UD*, *OUTLET*, and *GW\_DEPTH* as mentioned. Data from the first 5 months (from  
291 October 1, 2011 to February 29, 2012) were used for calibration, while those for the last 7 months (from

292 March 1 to September 30, 2012) were used for validation. Although both SWMM and MODFLOW were  
293 run at 5-min time steps, they were coupled hourly to save computations, so SWMM and MODFLOW each  
294 were run for 12 time steps before each round of data exchange. Updating groundwater table depths or  
295 recharge rates in SWMM and MODFLOW every hour was considered fine-grained enough to capture the  
296 surface runoff and groundwater table dynamics during the 1-year simulation. Particularly, the general  
297 groundwater level in the catchment does not fluctuate at a very fine scale according to historical monitoring  
298 (Herrera, 2013). It should be noted that the monitoring data used for model calibration was from the central  
299 catchment of the area (i.e., the CKCC site, red rectangular area in Fig. 4c). However, the model was built to  
300 cover the whole catchment and reach the catchment boundaries.

301 The calibration approach was similar to that of Zhang *et al.* (2018). More specifically, a non-dominated  
302 sorted genetic algorithm (NSGA-II) originally developed by Seshadri (2009) in MATLAB was utilized after  
303 integration with SWMM-MODFLOW. The parallel computing package of MATLAB was utilized, using  
304 four cores of the CPU to save computation time. The algorithm first initialized the parameters for calibration  
305 mentioned above, then invoked the execution of SWMM-MODFLOW. The Nash-Sutcliffe Efficiency (*NSE*)  
306 values of the datasets (i.e., *ROOF\_SR*, *IP\_SR*, *PP\_UD*, *OUTLET*, and *GW\_DEPTH*) were then computed as  
307 the performance indicators. Based on the objective of maximizing the performance indicators (i.e., the *NSE*  
308 values), the algorithm generated new populations (i.e., new sets of parameters) through the processes of  
309 parent selection, crossover (crossover probability = 0.9), and mutation (mutation probability = 0.1) out of  
310 the population generated (number of populations = 24). The parameters were improved after iterations of  
311 generations. The calibration was considered completed when the assigned total number of generations (10)  
312 was reached. This number of generations was sufficient because the *NSE* values of the datasets were found

313 to reach their near optimums after 8 generations. The final calibrated parameters were manually selected  
314 from the last generation of populations by striking a tradeoff among the *NSE* values of the datasets.

315 The SWMM parameters to be calibrated included underdrain coefficient, underdrain exponent, the  
316 offset height of underdrain, saturated hydraulic conductivity, the width of sub-catchment, Manning's *n* for  
317 overland flow, the depression storage of impervious area, and the roughness of the conduit. Additionally,  
318 hydraulic conductivity and specific yield were calibrated in MODFLOW.

319 **2.5 The hypothetical case studies**

320 A series of hypothetical scenarios were formulated to represent different spatial allocation patterns of  
321 BCs. One-year continuous simulations were then performed using the validated model, but with different  
322 spatial allocation patterns. The simulation duration was considered sufficient to capture the groundwater  
323 table dynamics because the response time of shallow groundwater was shorter, and the model was warmed  
324 up sufficiently. The results obtained were also considered representative given that the 1-year period covers  
325 a range of rainfall events and groundwater levels.

326 The initial conditions of the above simulations were the results from warm-up simulations in which  
327 there were no BCs. Using the 10-year rainfall from 2001 to 2011 in the study area as the input, the warm-up  
328 simulations were run repeatedly until they reached a dynamic equilibrium where the difference of  
329 groundwater levels, at 10 selected grids from different parts of the catchment between two consecutive  
330 simulations, was within 0.5%.

331 **2.5.1 Rules of spatial allocation of bioretention cells**

332 The rules of allocating the BCs within the catchment are illustrated in Fig. 5. The BCs were allocated

333 as a cluster of practices within each sub-catchment. The size of each BC was the same, and equal to the grid  
334 size of MODFLOW (23 m × 23 m). First, the number of BCs within each sub-catchment was determined,  
335 which represented the implementation ratio of the BCs. Then the central location of the BC cluster was  
336 determined (BC<sub>4</sub> in Fig. 5), which represented the approximate location of BCs within each sub-catchment.  
337 After that, the remaining BCs simply surrounded the central BC circle-by-circle, following a rectangular-  
338 shaped pattern until reaching the total number of BCs. A certain gap (i.e., 0–69 m in this study) was kept  
339 between each BC, the magnitude of which determined the aggregation level of the BC cluster. The physically  
340 unavailable locations, i.e., pervious areas and locations out of the sub-catchment, were skipped during the  
341 process (indicated by yellow cells with red crosses in Fig. 5). The spatial allocation assumed a uniform  
342 allocation pattern within each sub-catchment. This simplification is considered acceptable because this study  
343 focused on generating generic understanding instead of making detailed planning decisions. In addition, the  
344 surface flow routing between BCs was neglected, which may affect the runoff control performance of the  
345 BCs. This simplification was considered negligible because this study focused on groundwater table  
346 dynamics, and limited information about the site, such as topography, land use, and sewer systems, also  
347 hinders the consideration of flow routing between BCs.

348 Four dimensionless indicators (i.e., *RATIO*, *GAP*, *LOC<sub>c</sub>*, and *LOC<sub>sc</sub>*) were used to represent the  
349 different aspects of spatial allocation of BCs using equations shown in Fig. 5. These four indicators were  
350 selected because they represent the main factors that need to be considered in GI planning as proposed by  
351 Zhang and Chui (2018b):

352 • *RATIO* represents the implementation ratio of BCs, which is the ratio of the total area of BCs (*N\_GI<sub>n</sub>*)  
353 to the total area of available locations for BCs (*A<sub>n</sub>*) (Eq. 4).

354 •  $GAP$  represents the aggregation level of BCs, which is calculated by the ratio of average gap size

355 between BCs ( $L_{GAP}$ ) and the average size of BCs ( $L_{BC}$ ) (Eq. 5).

356 •  $LOC_c$  represents the relative location of BCs within the catchment, which ranges from 0 to 1. A

357 value closer to 0 or 1 means BCs are mainly allocated in upstream or downstream areas respectively. After

358 labeling the sub-catchments from 1 to  $N$  approximately from upstream to downstream, the relative location

359 index of each BC was calculated by dividing the index of the sub-catchment it belonged to ( $LOC_n$ ) by  $N$ .

360 Then  $LOC_c$  was obtained by taking the average of the relative location indices of all BCs (Eq. 6).

361 •  $LOC_{sc}$  represents the relative location of BCs within the sub-catchments, which ranges from 0 to 1.

362 Similar to  $LOC_c$ , a value closer to 0 or 1 means that BCs are mainly allocated near the upper or lower ends

363 of the sub-catchments, respectively. For a specific sub-catchment, the available locations for BCs were first

364 labeled from 1 to  $A_n$  approximately from upstream to downstream, and the relative location index of each

365 BC was calculated by dividing the index of the grid it belonged to ( $LOC_{BC_{m,n}}$ ) by  $A_n$ . Then the  $LOC_{sc}$  of

366 this sub-catchment was obtained by taking the average of the relative location indices of all BCs within this

367 sub-catchment (Eq. 7).

$$368 \quad RATIO = \frac{N_{BC_n}}{A_n} \quad (\text{Eq. 4})$$

$$369 \quad GAP = \frac{L_{GAP}}{L_{BC}} \quad (\text{Eq. 5})$$

$$370 \quad LOC_c = \frac{1}{\sum_{n=1}^N N_{BC_n}} \sum_{n=1}^N \frac{N_{BC_n} \times LOC_n}{N} \quad (\text{Eq. 6})$$

$$371 \quad LOC_{sc} = \frac{1}{\sum_{n=1}^N N_{BC_n}} \sum_{n=1}^N \sum_{m=1}^{N_{BC_n}} \frac{LOC_{BC_{m,n}}}{A_n} \quad (\text{Eq. 7})$$

372 where  $N$  represents the total number of sub-catchments (14 in this case);  $N_{BC_n}$  represents the total area of

373 BCs in sub-catchment  $n$ ;  $A_n$  represents the total area of available areas for BCs;  $L_{BC}$  and  $L_{GAP}$  represent the

374 size of BCs and the gap in between BCs, respectively;  $LOC_n$  represents the index of sub-catchment  $n$ ; and  
375  $LOC\_BC_{m,n}$  represents the index of the grid for the  $m^{th}$  BC in sub-catchment  $n$ . The exact ranges of these  
376 four indicators are elaborated in the next section.

377 The properties of the BCs, such as their thickness and the hydraulic conductivity of media soils,  
378 followed those of the BCs at the CKCC site mentioned above. More specifically, each BC constituted a 300  
379 mm soil layer and a 380 mm storage layer. Notably, however, no underdrain pipe was used. For each scenario,  
380 some sub-catchment parameters needed to be modified in SWMM. First, the width of the sub-catchments,  
381 which is one main parameter used to calculate overland flow in SWMM, was adjusted by multiplying the  
382 original value by the ratio of  $\frac{A_n - N\_BC_n}{A_n}$ , because a proportion of the impervious area was replaced by BCs.  
383 This approach is recommended in SWMM manuals and adopted by some SWMM users (Rossman, 2015).  
384 In addition, the percentage of the impervious area treated by BCs was also adjusted, allowing BCs to receive  
385 surface runoff from impervious areas that are, at most, 20 times larger. This is within the recommended range  
386 of most design standards, which range from 5 to 20 times the area of the BC (Dhalla and Zimmer, 2010;  
387 Roseen and Stone, 2013; Woods Ballard *et al.*, 2015).

### 388 2.5.2 Modeling scenarios and outputs

389 A total of 144 scenario-based simulations were performed to evaluate the impact of the spatial allocation  
390 of BCs on surface runoff and groundwater table dynamics. The scenarios covered four different  
391 implementation ratios of BCs ( $RATIO$  of 0.625%, 1.25%, 2.5%, and 5%); four different aggregation levels  
392 ( $GAP$  of 0, 1, 2, and 3); three different locations within the whole catchment ( $LOC_c$  of approximately 0.5,  
393 0.3, and 0.75 when BCs were distributed throughout all of the sub-catchments, only in upstream, or only in  
394 downstream sub-catchments, respectively); and three different locations within sub-catchments ( $LOC_{sc}$  of

395 approximately 0.1, 0.45, and 0.9 when BCs were allocated near the upper end, middle section, or lower end  
396 of sub-catchments, respectively). The ranges of parameters for the hypothetical scenarios are illustrated in  
397 Table 3 below.

398 The scenario without BCs was also simulated, and was treated as the base case. The indicators  
399 representing the surface runoff and groundwater table dynamics were then calculated by comparing the  
400 results of the base case with those of the hypothetical cases. More specifically, the peak reduction ( $PR$ ) and  
401 volume reduction ( $VR$ ) of surface runoff throughout the year in different sub-catchments, and for the whole  
402 catchment, were extracted to represent the surface runoff dynamics. The peak ( $GR_P$ ) and temporally averaged  
403 ( $GR_M$ ) groundwater table rises in different sub-catchments and for the whole catchment, as well as the  
404 standard deviation of groundwater level in the catchment ( $GL_{STD}$ ) throughout the year, were extracted to  
405 represent the groundwater table dynamics. The three parameters together can comprehensively represent the  
406 local and regional changes of groundwater levels, as well as the uniformity of groundwater levels. Note that  
407 higher runoff control efficiency (i.e., higher  $PR$  and  $VR$ ) and more spatially uniform groundwater levels (i.e.,  
408 lower  $GR_P$ ,  $GR_M$ , and  $GL_{STD}$ ) are generally preferred, because a more uniform groundwater level results  
409 from higher recharge in areas with a deeper groundwater table and lower recharge in areas of a shallower  
410 groundwater table. The outcome is beneficial because the two objectives of enhancing groundwater recharge  
411 in deeper areas and minimizing groundwater mounding in shallow groundwater areas can be realized  
412 simultaneously.

413

414 **3. Results and discussion**

415 **3.1. Model calibration and validation**

416 Fig. 6 shows the time series of different datasets (i.e., rainfall, *PP\_UD*, *IP\_SR*, *ROOF\_SR*, *OUTLET*,  
417 and *GW\_DEPTH*) during both calibration and validation periods. The light gray and dark gray sections in  
418 Fig. 6a-6f correspond to the calibration and validation periods, respectively. One event on December 23,  
419 2011 is shown specifically in Fig. 6g-6l. This event is considered representative given its medium rainfall  
420 intensity (12 mm/h), runoff amount (23 mm), and groundwater table fluctuation (0.3 m) during the period,  
421 which can be observed in Fig. 6. In addition, the final calibrated parameters in both SWMM and MODFLOW  
422 are shown in Table 4 and are all within physically reasonable ranges.

423 The pipe flow at the outlet of the catchment (*OUTLET*) and surface runoff of the building roof  
424 (*ROOF\_SR*) showed very good fits with the monitoring data, with *NSE* of 0.80 and 0.62 during calibration,  
425 and 0.64 and 0.51 during validation, respectively (Fig. 6d and 6e). The underdrain flow (*PP\_UD*) and surface  
426 runoff (*IP\_SR*) were slightly underestimated at rainfall peaks and rises of the groundwater table (Fig. 6h and  
427 6i), but were still of reasonable goodness of fit. The *NSE* of *PP\_UD* and *IP\_SR* were 0.44 and 0.42 during  
428 calibration, and 0.50 and 0.41 during validation, respectively. Particularly, the goodness of fit of *PP\_UD* was  
429 improved during the selected event with an *NSE* of 0.72 (Fig. 6h). Generally, the goodness of fit values of  
430 these datasets were acceptable, and comparable to those obtained by Zhang *et al.* (2018) using SWMM-LID-  
431 GW with groundwater monitoring data as direct input.

432 Comparatively, the goodness of fit for *GW\_DEPTH* was not as satisfactory, with *NSE* values of -0.26  
433 and 0.33 during calibration and validation periods, respectively (Fig. 6f). However, SWMM-MODFLOW  
434 captured the general fluctuations of the groundwater table during the overall period and the selected event

435 (Fig. 6f and 6l), and the goodness of fit during the selected event was reasonable (NSE of 0.61) (Fig. 6l).  
436 The good fits of *PP\_UD* and *OUTLET* also confirmed the accuracy of groundwater simulation to some  
437 extent, because they are both highly related to groundwater table depth, as shown in Zhang *et al.* (2018). The  
438 discrepancy could be reduced if there were additional monitoring data for model calibration, and if a better  
439 understanding of the spatial variations of subsurface geophysical conditions (e.g., hydraulic conductivity and  
440 specific yield) in the study area could be obtained.

441 **3.2. Surface runoff dynamics**

442 Fig. 7 shows the surface runoff response, represented by peak reduction (*PR*) and volume reduction  
443 (*VR*) of surface runoff, at different sub-catchments for different implementation ratios of BCs. It should be  
444 noted that the values shown in the graph (Fig. 7) are the averaged results of different scenarios. Fig. 7  
445 explicitly shows the results for different values of *RATIO*, but the *RATIO* values in the graph are the  
446 averaged results for different values of *GAP*, *LOC<sub>C</sub>*, and *LOC<sub>SC</sub>*. This also applies to other similar graphs (i.e.,  
447 Fig. 8-13).

448 As expected, *PR* and *VR* were greater when there were more BCs. More specifically, when the  
449 implementation ratio of BCs increased from 0.625% to 1.25%, 2.50%, and 5.00%, respectively, *PR* for the  
450 whole area (shown as dashed lines in Fig. 7b) increased from  $1.9 \pm 1.3\%$  to  $8.6 \pm 2.7\%$ ,  $22.3 \pm 2.8\%$ , and  
451  $43.6 \pm 4.8\%$ , and *VR* for the whole area (shown as dashed lines in Fig. 7d) increased from  $4.2 \pm 1.7\%$  to  
452  $15.1 \pm 2.7\%$ ,  $35.2 \pm 3.1\%$ , and  $54.5 \pm 13.5\%$ . Considering that this is a highly impermeable catchment  
453 (approximately 80% urbanized), the impact of BCs may not be as significant for other more permeable  
454 catchments.

455 Furthermore, it was found that the impact of the implementation ratio was different in different sub-

456 catchments. Using the scenario of an implementation ratio of 5.00% as an example, the  $PR$  values of sub-  
457 catchments S7, S8, and S9 were  $56.7 \pm 41.2\%$ ,  $53.9 \pm 40.6\%$ , and  $52.2 \pm 39.9\%$ , which were significantly  
458 higher than the  $PR$  values of sub-catchments S1, S4, S10, and S14, which were approximately  $0.0 \pm 0.0\%$ ,  
459  $30.4 \pm 26.2\%$ ,  $43.3 \pm 37.0\%$ , and  $32.9 \pm 30.7\%$ , respectively (Fig. 7b). This was also true for the  $VR$  values  
460 (Fig. 7d). These sub-catchment differences were likely caused by differences of imperviousness, slope, and  
461 the permeability of in-situ soils. Compared with the imperviousness values of sub-catchments S7, S8, and  
462 S9 (57%, 50.7%, and 66.2%, respectively), the imperviousness values of sub-catchments S4, S10, and S14  
463 were higher (79.1%, 95.3%, and 78.7%, respectively), and the soils of sub-catchments S4, S10, and S14,  
464 which are near the two rivers and the sea, are of lower permeability than the other sub-catchments, which  
465 resulted in lower runoff control efficiency in these areas. Although sub-catchment S1 was lower in  
466 imperviousness (i.e., 47.5%), its slope (i.e., 14%) was significantly greater than that of other sub-catchments,  
467 which was not beneficial for runoff control. This was consistent with the mechanisms of GI and runoff  
468 generation found in some other studies (Shuster *et al.*, 2005; Dietz and Clausen, 2008; Ahiablame and Shakya,  
469 2016).

470 **3.3. Groundwater table dynamics**

471 Figs. 8-13 compare the response of the groundwater table with BCs of different spatial allocations. More  
472 specifically, Figs. 8, 11, 12, and 13 show the spatial variation of peak ( $GR_P$ ) and temporally averaged ( $GR_M$ )  
473 groundwater table rises within the catchment. Fig. 9 shows the spatial variation of mean groundwater table  
474 depth throughout the year, and Fig. 10 illustrates the standard deviation of groundwater levels in the  
475 catchment ( $GL_{STD}$ ) throughout the year.

476 3.3.1. Impact of the implementation ratio of bioretention cells

477 A small number of BCs can significantly change the groundwater dynamics. For example, when  
478 averaged over the whole catchment, if 0.625%, 1.25%, 2.50%, and 5.00% of the impervious area were  
479 replaced by BCs, the peak groundwater rise ( $GR_P$ ) would be approximately  $0.13 \pm 0.05$  m,  $0.34 \pm 0.08$  m,  
480  $0.82 \pm 0.11$  m, and  $1.31 \pm 0.38$  m, respectively (see dashed lines in Fig. 8b and Fig. 8c). At some specific  
481 locations, the groundwater table rise can be a few meters or higher ( $> 5$  m) during some specific time (Fig.  
482 8d). This is a significant change and can be problematic, considering that the thickness of the unsaturated  
483 zone was only from 0 to 5 m in approximately half of the catchment, and 5 out of 14 sub-catchments had  
484 groundwater tables very close to the ground (Fig. 9b). In addition, it was found that BCs not only affect the  
485 local groundwater table, but also influence regional groundwater levels. When 5% of the catchment was  
486 replaced by BCs, the groundwater table of the catchment was as much as 1 m closer to the ground compared  
487 with an implementation ratio of 0.625% (Fig. 9c). This can also be seen from the significantly large areas of  
488 groundwater table rise (darker green regions) shown in Fig. 8a and 8d. A similar observation was obtained  
489 by Bhaskar *et al.* (2018). This illustrates the importance of considering the groundwater table condition in  
490 the spatial planning of GI.

491 Fig. 8d and 8h show the exceedance probability curves of  $GR_P$  and  $GR_M$  within the catchment,  
492 illustrating the proportion of the catchment area with different levels of  $GR_P$  and  $GR_M$ . Similarly, Fig. 11d,  
493 11h, 12d, 12h, 13d, and 13h illustrate the same information. They provide another perspective on the  
494 groundwater table dynamics as a result of BCs. With more BCs implemented, the proportion of catchment  
495 areas with lower groundwater rises (e.g.,  $< 1.0$  m for peak rise and  $< 0.4$  m for temporally averaged rise) was  
496 lower, while the proportion of catchment areas with higher groundwater rises (e.g.,  $> 1.0$  m for peak rise

497 and > 0.4 m for temporally averaged rise) was higher (Fig. 8d and 8h). For example, when only 0.625% of  
498 the impervious area was replaced by BCs, approximately 100% of the catchment had a  $GR_P$  of less than 1.0  
499 m and a  $GR_M$  less than 0.2 m. However, when 5.00% of the catchment was replaced by BCs, only 48% and  
500 39% of the catchment had  $GR_P$  and  $GR_M$  values less than 1.0 m and 0.2 m, respectively. Overall, areas  
501 comprising 33%, 14%, 4%, and 2% of the catchment had  $GR_P$  values of 1–2 m, 2–3 m, 3–4 m, and 4–5 m,  
502 respectively (Fig. 8d and 8h).

503 Similar to surface runoff, the groundwater table response also varied among different sub-catchments.  
504 Comparatively, sub-catchments around the center of the catchment (e.g., S3 and S9) showed higher  
505 groundwater table rises than those closer to the catchment boundary (e.g., S1 and S14) (Fig. 8b and 8f). A  
506 similar observation can be obtained from Fig. 11–13. This variation can be explained by noting that the  
507 upstream areas were of steeper topography and groundwater hydraulic gradients, while the downstream areas  
508 were of gentler topography and groundwater hydraulic gradients. As a result, the groundwater tended to  
509 gather in the central sub-catchments (e.g., S3 and S9), rather than sub-catchments nearer the boundary. This  
510 is quite a common phenomenon in sloped areas. Focusing on a catchment of similar terrain (i.e., steeper or  
511 gentler in upstream or downstream directions, respectively) in China, Cai *et al.* (2015) also found that the  
512 groundwater level was higher in the medium section of the catchment. However, the same phenomenon may  
513 not occur in catchments of different topographies. For example, a more uniform groundwater table rise is  
514 expected in relatively flat catchments.

515 Notably, increasing the implementation level of BCs could slightly decrease the average uniformity of  
516 the groundwater table due to the greater maximum and minimum  $GL_{STD}$  values (Fig. 10a), although the  
517 differences were not that significant. During approximately 50% of the time, the uniformity of the

518 groundwater table condition among different implementation ratios was very similar (Fig. 10a). Thus,  
519 implementing more BCs with an appropriate allocation strategy may not be unfavorable to the regional  
520 groundwater dynamics.

521 3.3.2. Impact of the aggregation level of bioretention cells

522 Fig. 11 compares the response of the groundwater table to different aggregation levels of BCs. The  
523 spatial variation in groundwater table rise was different for different BC aggregation levels, particularly for  
524  $GR_P$  (Fig. 11a). When BCs were more aggregated, with a smaller  $GAP$ , the groundwater table rises were also  
525 more concentrated (Fig. 11a). As a result, BCs allocated in a more aggregated pattern formed slightly higher  
526  $GR_P$  for the overall catchment (the dashed lines in Fig. 11b and Fig. 11c).  $GR_P$  of the catchment was  $0.70 \pm$   
527  $0.55$  m,  $0.66 \pm 0.51$  m,  $0.65 \pm 0.50$  m, and  $0.64 \pm 0.48$  m when  $GAP$  was 0, 1, 2, and 3, respectively. This  
528 was expected because more densely aggregated BCs with a relatively short distance between them may form  
529 an overlapped groundwater mound (Endreny and Collins, 2009). When the BCs were more aggregated, the  
530 proportion of lower  $GR_P$  areas was smaller, while that of higher  $GR_P$  areas was greater (Fig. 11d). For the  
531 same reason, the  $GL_{STD}$  of the catchment was slightly higher when the BCs were allocated in a more  
532 aggregated pattern (Fig. 10b).

533 However,  $GR_M$  for the catchment was slightly greater when the BCs were allocated in a more distributed  
534 pattern (Fig. 11f). When the BCs were more distributed, the proportion of lower  $GR_M$  areas was smaller,  
535 while the proportion of higher  $GR_M$  areas was greater (Fig. 11h), which was different from the pattern in Fig.  
536 11d. This is possibly because more distributed BCs can affect a greater proportion of the total area. This can  
537 be seen from the spatial variation of  $GR_M$  of the catchment, in which the shaded areas are larger when  $GAP$   
538 is greater (Fig. 11e). As a result, the overall groundwater table rise of the catchment was higher, although

539 with a relatively low local groundwater table rise at specific locations. However, the impact of the  
540 aggregation level on the regional groundwater table dynamics was relatively minimal, compared with that  
541 of the implementation level. This can be seen from the minimal difference in groundwater table depth shown  
542 in Fig. 9d.

543 Thus, to achieve a more spatially uniform groundwater level, which is a generally desired condition,  
544 BCs with more distributed patterns are preferred when the groundwater table depth is relatively uniform.  
545 When BCs need to be allocated in a more aggregated pattern, due to site constraints, it would be better if  
546 they could be allocated in places with a deeper groundwater table.

547 3.3.3. Impact of the location of bioretention cells

548 Figs. 12 and 13 compare the responses of the groundwater table to BCs allocated at different locations  
549 within the catchment and within sub-catchments, respectively. When the BCs were spatially distributed, or  
550 in upstream areas of the catchment,  $GR_P$  and  $GR_M$  were greater than when the BCs were in downstream  
551 areas. When the BCs were spatially distributed, only in upstream areas, or only in downstream areas, the  
552 corresponding  $GR_P$  for the whole catchment was  $0.72 \pm 0.66$  m,  $0.70 \pm 0.47$  m, or  $0.54 \pm 0.33$  m,  
553 respectively (dashed lines in Fig. 12b and Fig. 12c), and the  $GR_M$  for the whole catchment was 0.45 m, 0.46  
554 m, or 0.31 m, respectively (dashed lines in Fig. 12f and Fig. 12g). In addition, the proportion of areas of  
555 lower groundwater table rise (both  $GR_P$  and  $GR_M$ ) was smaller, and the proportion of areas of higher  
556 groundwater table rise was greater, when the BCs were spatially distributed or only in upstream areas (Fig.  
557 12d and 12h).

558 These phenomena have two possible explanations. First, as shown in Fig. 9, the groundwater table in  
559 upstream areas (i.e., S1, S3, S4, S5, and S6) was closer to the ground surface, so the groundwater table could

560 respond and rise more quickly and more significantly. Second, the regional groundwater hydraulic gradient  
561 may play a role. Generally, the recharge from BCs in upstream areas can affect the groundwater table  
562 conditions in downstream areas more quickly and to a larger spatial extent, while the recharge in downstream  
563 areas normally extends to the surrounding areas without obvious directionality. This can be seen clearly in  
564 Fig. 11b and 11f. When the BCs were allocated in upstream sub-catchments (S1-S7), obvious groundwater  
565 table rises were observed in some downstream sub-catchments (S8-S10). In contrast, when the BCs were  
566 allocated in downstream sub-catchments (i.e., S8-S14), the groundwater table also rose at some of the  
567 upstream sub-catchments (i.e., S2, S3, and S7) but the rise was relatively minimal. However, the magnitude  
568 of this effect may differ for different regional groundwater hydraulic gradients and hydrologic connectivities  
569 (Jones *et al.*, 2019). For example, the effect may not be as significant in areas with relatively flat topographies.

570 A similar phenomenon was observed through comparing the  $GR_M$  values for BCs allocated at different  
571 locations within sub-catchments (Fig. 13). Compared with BCs at the lower end of the sub-catchments ( $0.31$   
572  $\pm 0.22$  m),  $GR_M$  for the overall catchment was greater when the BCs were at the upper end or in the middle  
573 section of the sub-catchments ( $0.44 \pm 0.32$  m and  $0.46 \pm 0.36$  m, respectively) (Fig. 13f and 13g), because  
574 the proportion of higher  $GR_M$  areas was greater (Fig. 13h). In addition, the groundwater levels within the  
575 catchment were less uniform (represented by larger  $GL_{STD}$  values) when the BCs were allocated in upstream  
576 areas and near the upper end of sub-catchments, and vice versa (Fig. 10c and 10d).

577 Thus, when the groundwater table is relatively deep, BCs are generally better allocated in upstream  
578 areas to result in greater regional groundwater recharge and groundwater table rise. When the groundwater  
579 table is relatively shallow, it is generally better to allocate BCs in the downstream areas to minimize  
580 groundwater table rise and its potential effects on the performance of BCs. However, the optimal allocation

581 may vary case-by-case, as other geophysical conditions like soil distribution should also be considered.  
582 Furthermore, it was found that both  $GR_P$  and  $GR_M$  of upstream sub-catchments (S1-S7) were greater when  
583 the BCs were allocated at the upper end of the sub-catchments. These values for downstream sub-catchments  
584 (S9-S14) were greater when the BCs were allocated at the lower end of the sub-catchments (Fig. 13b and  
585 13f). For example, when the BCs were located at the upper end, middle section, and lower end,  $GR_P$  of S2  
586 decreased from approximately  $1.01 \pm 0.86$  m to  $0.68 \pm 0.61$  m and  $0.51 \pm 0.61$  m, respectively (Fig. 13b  
587 and 13c), and  $GR_M$  of S2 decreased from  $0.67 \pm 0.62$  m to  $0.47 \pm 0.43$  m and  $0.30 \pm 0.38$  m, respectively  
588 (Fig. 13f and 13g). In comparison,  $GR_P$  of S9 increased from  $0.72 \pm 0.65$  m to  $1.03 \pm 0.93$  m and  $1.38 \pm$   
589 1.23 m, respectively (Fig. 13b and 13c), and  $GR_M$  of S9 increased from  $0.43 \pm 0.39$  m to  $0.54 \pm 0.42$  m and  
590  $0.61 \pm 0.46$  m, respectively (Fig. 13f and 13g). This was because the extent of groundwater rise was greater  
591 near BCs (Machusick *et al.*, 2011; Thomas and Vogel, 2011; Nemirovsky *et al.*, 2014). More specifically,  
592 when the BCs (in all sub-catchments) were allocated at the upper end of each sub-catchment, those within  
593 the downstream sub-catchments were closer to the upstream sub-catchments. Therefore, the groundwater  
594 recharge by BCs in downstream sub-catchments more easily affected upstream sub-catchments, resulting in  
595 higher groundwater table rises in upstream areas. Conversely, when the BCs were allocated at the lower end  
596 of each sub-catchment, those within the upstream sub-catchments were closer to the downstream sub-  
597 catchments. Then the groundwater recharge by BCs in upstream sub-catchments more easily affected  
598 downstream sub-catchments, resulting in higher groundwater table rise in downstream areas.

599 **3.4. Relationships between surface runoff and groundwater table dynamics**

600 Fig. 14 illustrates the inter-correlations between the responses of surface runoff and groundwater table  
601 levels to different implementation ratios of BCs. Each dot in the graph represents the data ( $PR$ ,  $VR$ ,  $GR_P$ ,

602  $GR_M$ , or  $GL_{STD}$ ) for one sub-catchment.

603 One observation can be obtained from the bar plots along the diagonal of Fig. 14. More specifically,  
604 when there were more BCs (*RATIO* of 5.00%), the occurrences of higher  $PR$ ,  $VR$ ,  $GR_P$ ,  $GR_M$ , and  $GL_{STD}$   
605 values were greater, which was consistent with observations in previous sections. As expected,  $PR$  and  $VR$   
606 correlated with each other closely, with an  $R^2$  of 0.95. For groundwater table rises, only  $GR_P$  and  $GR_M$  were  
607 closely correlated ( $R^2$  of 0.91), while  $GL_{STD}$  was less correlated to the other two indicators ( $R^2$  of 0.59 and  
608 0.42 for  $GR_P$  and  $GR_M$  respectively). In addition, the indicators of surface runoff (i.e.,  $PR$  and  $VR$ ) were also  
609 correlated with the indicators of groundwater table rises (i.e.,  $GR_P$ ,  $GR_M$ , and  $GL_{STD}$ ) at a relatively lower,  
610 but still significant, level (Fig. 14). More specifically,  $PR$  correlated with  $GR_P$ ,  $GR_M$ , and  $GL_{STD}$  with  $R^2$   
611 values of 0.85, 0.82, and 0.45, respectively, and  $VR$  correlated with  $GR_P$ ,  $GR_M$ , and  $GL_{STD}$  with  $R^2$  values of  
612 0.86, 0.84, and 0.45, respectively. The observed correlations were not surprising, because the reduction of  
613 surface runoff and the increase of groundwater recharge were simultaneous outcomes of enhanced  
614 infiltration and recharge by GI.

615 These observations together reflect the importance of considering the tradeoffs between surface runoff  
616 control and groundwater protection in GI planning. A more ideal GI strategy should reduce surface runoff,  
617 but also maintain a relatively minimal influence on groundwater dynamics.

618

#### 619 **4. Concluding remarks**

620 A coupled surface-subsurface hydrological model, SWMM-MODFLOW, was developed to evaluate  
621 the surface runoff and groundwater table dynamics of green infrastructure of different spatial allocations at

622 catchment scale. The model was calibrated and validated using the monitoring data at an urban catchment at  
623 Kitsap County, WA, US.

624 Using bioretention cells as the representative green infrastructure, a series of hypothetical simulations  
625 was performed. The influence of spatial allocations of bioretention cells, represented by the implementation  
626 ratio, aggregation level, and location, on the surface runoff and groundwater table dynamics, was quantified.  
627 The primary findings are summarized as follows.

628 • The implementation ratio of the bioretention cells was the main spatial feature that governed both surface  
629 runoff and groundwater table dynamics. With higher implementation ratios, the peak reduction and  
630 volume reduction of surface runoff were greater, and the peak and temporally averaged groundwater  
631 table rises were higher. However, implementing more bioretention cells may not affect the uniformity  
632 of regional groundwater levels if an appropriate allocation strategy is selected.

633 • Bioretention cells with more distributed allocation patterns resulted in slightly lower peak groundwater  
634 table rises, higher temporally averaged groundwater table rises, and a lower standard deviation of  
635 groundwater levels in the catchment. Thus, if a more uniform groundwater level is desired, bioretention  
636 cells should be allocated in a more distributed way when the original groundwater table depth is  
637 relatively uniform. Conversely, when bioretention cells need to be allocated in a more aggregated pattern  
638 (e.g., due to site constraints), it would be better if they could be allocated in places with a deeper  
639 groundwater table.

640 • Allocating bioretention cells in upstream areas can raise the groundwater levels downstream due to the  
641 regional hydraulic gradient. Thus, when the groundwater table is relatively deep, bioretention cells  
642 should generally be allocated in upstream areas to produce a greater regional groundwater recharge and

643 groundwater table rise. In cases when the groundwater table is relatively shallow, it is generally better  
644 to implement bioretention cells in the downstream areas to minimize groundwater table rise and the  
645 potential influence on the performance of bioretention cells. In addition, the geophysical conditions and  
646 spatial variations within the catchment should be considered when allocating bioretention cells.

647 • Bioretention cells of greater surface runoff control efficiencies led to higher groundwater table rises.  
648 Thus, it is of great importance to consider the tradeoff between surface runoff control and groundwater  
649 protection in the planning of green infrastructure.

650 This study carries certain limitations. First, the coupled model considered the impact of shallow  
651 groundwater on some hydrological processes such as exfiltration, underdrain flow, and surface runoff, but  
652 other processes were neglected. For example, the impact of shallow groundwater on evapotranspiration of  
653 GI was not considered, which could be influential in some conditions such as areas of shallow groundwater  
654 or arid climate. Second, the rules for allocating bioretention cells spatially in the hypothetical simulations  
655 were simplified. The detailed land uses (e.g., buildings, roads) and physical constraints (e.g., underground  
656 infrastructures) were not considered due to the unavailability of relevant information, so a relatively uniform  
657 allocation pattern was assumed. As a result, the main insights obtained in this study may have limited  
658 contribution at the scales of single GI practices, but they can be beneficial to the higher-level planning of GI.

659 The simplified rule of spatial allocation of GI practices therefore should not affect the insights that work at  
660 regional scales. In fact, considering the specific physical and/or legal constraints of the study area might  
661 even have affected the transferability of the insights gained, because the constraints can be very different in  
662 different areas. Third, the simulations in this study only considered the boundary conditions and  
663 hydrogeological conditions of one catchment due to data availability. However, the results from this study

664 can serve as a general reference for others, and the developed model and study methodology can be applied  
665 to other catchments to obtain more specific and accurate findings. Future studies should examine more  
666 catchment characteristics, such as through the use of more hypothetical catchments, and more spatial  
667 allocation rules for various GI practices. They should also explore the optimal spatial allocation of green  
668 infrastructure for the restoration of surface-subsurface hydrology.

669

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674

## 675 **References**

676 Ahiablame, L. and Shakya, R., 2016. Modeling flood reduction effects of low impact development at a watershed  
677 scale. *J. Environ. Manage.*, 171, 81-91.

678 Avellaneda, P.M., Jefferson, A.J., Grieser, J.M. and Bush, S.A., 2017. Simulation of the cumulative hydrological  
679 response to green infrastructure. *Water Resour. Res.*, 53(4), 3087-3101.

680 Barron, O.V., Barr, A.D. and Donn, M.J., 2013. Effect of urbanisation on the water balance of a catchment with  
681 shallow groundwater. *J. Hydrol.*, 485, 162-176.

682 Bhaskar, A.S., Hogan, D.M. and Archfield, S.A., Urban base flow with low impact development. *Hydrol.*

683        *Process.*, **30**(18), 2016, 3156-3171.

684        Bhaskar, A.S., Hogan, D.M., Nimmo, J.R., and Perkins, K.S., Groundwater recharge amidst focused stormwater  
685        infiltration. *Hydrol. Process.*, **32**, 2018, 2058-2068.

686        Bradshaw, J.L. and Luthy, R.G., Modeling and optimization of recycled water systems to augment urban  
687        groundwater recharge through underutilized stormwater spreading basins. *Environ. Sci. & Technol.*, **51**(20),  
688        2017, 11809-11819.

689        Brown, R.R., Keath, N. and Wong, T.H., Urban water management in cities: historical, current and future  
690        regimes. *Water Sci. Technol.*, **59**(5), 2009, 847-855.

691        Chen, L., Qiu, J., Wei, G. and Shen, Z., A preference-based multi-objective model for the optimization of best  
692        management practices. *J. Hydrol.*, **520**, 2015, 356-366.

693        Chen, L., Wei, G. and Shen, Z., Incorporating water quality responses into the framework of best management  
694        practices optimization. *J. Hydrol.*, **541**, 2016, 1363-1374.

695        Chiang, L.C., Chaubey, I., Maringanti, C. and Huang, T., Comparing the selection and placement of best  
696        management practices in improving water quality using a multiobjective optimization and targeting method.  
697        *Int. J. Env. Res. Pub. He.*, **11**(3), 2014, 2992-3014.

698        Chui, T.F.M., Liu, X. and Zhan, W., Assessing cost-effectiveness of specific LID practice designs in response to  
699        large storm events. *J. Hydrol.*, **533**, 2016, 353-364.

700        Chui, T.F.M. and Trinh, D.H., Modelling infiltration enhancement in a tropical urban catchment for improved  
701        stormwater management. *Hydrol. Process.*, **30**(23), 2016, 4405-4419.

702 Damodaram, C. and Zechman, E.M., Simulation-optimization approach to design low impact development for  
703 managing peak flow alterations in urbanizing watersheds. *J. Water Resour. Plan. Manage.*, **139**(3), 2012,  
704 290-298.

705 Datry, T., Malard, F. and Gibert, J., Dynamics of solutes and dissolved oxygen in shallow urban groundwater  
706 below a stormwater infiltration basin. *Sci. Total Environ.*, **329**(1-3), 2004, 215-229.

707 Dhalla, S. and Zimmer, C., 2010. *Low Impact Development Stormwater Management Planning and Design*  
708 *Guide*. Toronto and Toronto and Region Conservation Authority: Toronto, ON, Canada, 300.

709 Dietz, M.E. and Clausen, J.C., 2008. Stormwater runoff and export changes with development in a traditional and  
710 low impact subdivision. *J. Environ. Manage.*, **87**(4), 560-566.

711 Dussaillant, A.R., Wu, C.H. and Potter, K.W., 2004. Richards equation model of a rain garden. *J. Hydrol.*  
712 *Eng.*, **9**(3), 219-225.

713 EC-European Commission, *Green Infrastructure (GI)—Enhancing Europe's Natural Capital*. European  
714 Commission, 2013, Brussels.

715 Elliott, A.H., Trowsdale, S.A. and Wadhwa, S., Effect of aggregation of on-site storm-water control devices in an  
716 urban catchment model. *J. Hydrol. Eng.*, **14**(9), 2009, 975-983.

717 Endreny, T. and Collins, V., Implications of bioretention basin spatial arrangements on stormwater recharge and  
718 groundwater mounding. *Ecol. Eng.*, **35**(5), 2009, 670-677.

719 Fischer, D., Charles, E.G. and Baehr, A.L., Effects of stormwater infiltration on quality of groundwater beneath  
720 retention and detention basins. *J. Environ. Eng.*, **129**(5), 2003, 464-471.

721 Fletcher, T.D., Shuster, W., Hunt, W.F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-

722 Davies, A., Bertrand-Krajewski, J.-L., Mikkelsen, P.S., Rivard, G., Uhl, M., Dagenais, D., Viklander, M.,

723 SUDS, LID, BMPs, WSUD and more – the evolution and application of terminology surrounding urban

724 drainage. *Urban Water J.*, **12**(7), 2015, 525–542.

725 Giacomoni, M.H. and Joseph, J., Multi-Objective Evolutionary Optimization and Monte Carlo Simulation for

726 Placement of Low Impact Development in the Catchment Scale. *J. Water Resour. Plan. Manage.*, **143**(9),

727 2017, 04017053.

728 Göbel, P., Stubbe, H., Weinert, M., Zimmermann, J., Fach, S., Dierkes, C., Kories, H., Messer, J., Mertsch, V.,

729 Geiger, W.F. and Coldewey, W.G., Near-natural stormwater management and its effects on the water budget

730 and groundwater surface in urban areas taking account of the hydrogeological conditions. *J. Hydrol.*, **299**(3-4), 2004, 267-283.

731 He, Z., Davis, A.P., Process modeling of storm-water flow in a bioretention cell. *J. Irrig. Drain. Eng.* **137**(3), 2010,

732 121–131.

733 Herrera, 2013. *Central Kitsap community campus low impact development flow monitoring project, Final project report*. Prepared for Kitsap County Public Works (Surface and Stormwater management program), Port

734 Orchard, Washington, by Herrera Environmental Consultants, Inc., Seattle, Washington. Feb 4, 2013.

735 Hoghooghi, N., Golden, H.E., Bledsoe, B.P., Barnhart, B.L., Brookes, A.F., Djang, K.S., Halama, J.J., McKane,

736 R.B., Nietch, C.T., Pettus, P.P., Cumulative effects of low impact development on watershed hydrology in a

737 mixed land-cover system. *Water*, **10**, 2018, 991.

738 Jayasooriya, V.M., Ng, A.W.M., Muthukumaran, S., Perera, B.J.C., Optimal sizing of green infrastructure

741 treatment trains for stormwater management. *Water Resour. Manag.* **30**, 2016, 5407–5420.

742 Jefferson, A.J., Bhaskar, A.S., Hopkins, K.G., Fanelli, R., Avellaneda, P.M. and McMillan, S.K., Stormwater  
743 management network effectiveness and implications for urban watershed function: A critical review. *Hydrol.*  
744 *Process.*, **31**, 2017, 4056– 4080.

745 Johnson, R.D., Sample, D.J., A semi-distributed model for locating stormwater best management practices in  
746 coastal environments. *Environ. Model. Softw.* **91**, 2017, 70-86.

747 Jones, C.N., Ameli, A., Neff, B.P., Evenson, G.R., McLaughlin, D.L., Golden, H.E., and Lane, C.R., Modeling  
748 Connectivity of Non-floodplain Wetlands: Insights, Approaches, and Recommendations. *J. Am. Water  
749 Resour. As.*, 2019, 1– 19.

750 Kong, F., Ban, Y., Yin, H., James, P., Dronova, I., Modeling stormwater management at the city district level in  
751 response to changes in land use and low impact development. *Environ. Model. Softw.* **95**, 2017, 132–142.

752 Lauvernet, C. and Muñoz-Carpena, R., Shallow water table effects on water, sediment, and pesticide transport in  
753 vegetative filter strips—Part 2: model coupling, application, factor importance, and uncertainty. *Hydrol. Earth  
754 Syst. Sci.*, **22**(1), 2018, 71-87.

755 Lee, J.G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J.X., Shoemaker, L. and Lai, F.H., A watershed-scale  
756 design optimization model for stormwater best management practices. *Environ. Model. & Softw.*, **37**, 2012,  
757 6-18.

758 Lee, J., Shuster, W., and Kshirsagar, S., Need to improve SWMM's subsurface flow routing algorithm for green  
759 infrastructure modeling. *51st International Conference On Water Management Modeling, Toronto, Ontario,*  
760 *CANADA, February 28 - March 01, 2018.*

761 Lim, T.C., 2016. Predictors of urban variable source area: a cross-sectional analysis of urbanized catchments in  
762 the United States. *Hydrol. Process.*, **30**(25), 4799-4814.

763 Lim, T.C. and Welty, C., 2017. Effects of spatial configuration of imperviousness and green infrastructure  
764 networks on hydrologic response in a residential sewershed. *Water Resour. Res.*, **53**(9), 8084-8104.

765 Liu, Y., Cibin, R., Bralts, V.F., Chaubey, I., Bowling, L.C. and Engel, B.A., Optimal selection and placement of  
766 BMPs and LID practices with a rainfall-runoff model. *Environ. Model. & Softw.*, **80**, 2016, 281-296.

767 Liu, Y., Theller, L.O., Pijanowski, B.C. and Engel, B.A., Optimal selection and placement of green infrastructure  
768 to reduce impacts of land use change and climate change on hydrology and water quality: An application to  
769 the Trail Creek Watershed, Indiana. *Sci. Total Environ.*, **553**, 2016, 149-163.

770 Locatelli, L., Mark, O., Mikkelsen, P.S., Arnbjerg-Nielsen, K., Wong, T. and Binning, P.J., Determining the extent  
771 of groundwater interference on the performance of infiltration trenches. *J. Hydrol.*, **529**, 2015, 1360-1372.

772 Lucas, W.C., Sample, D.J., Reducing combined sewer overflows by using outlet controls for green stormwater  
773 infrastructure: case study in Richmond, Virginia. *J. Hydrol.* **520**, 2015, 473-488.

774 Machusick, M., Welker, A. and Traver, R., Groundwater mounding at a storm-water infiltration BMP. *J. Irrig.*  
775 *Drain. Eng.*, **137**(3), 2011, 154-160.

776 Macro, K., Matott, L.S., Rabideau, A., Ghodsi, S.H. and Zhu, Z., OSTRICH-SWMM: A new multi-objective  
777 optimization tool for green infrastructure planning with SWMM. *Environ. Model. & Softw.*, **113**, 2019, 42-  
778 47.

779 Mao, X., Jia, H. and Shaw, L.Y., Assessing the ecological benefits of aggregate LID-BMPs through modelling.  
780 *Ecol. Model.*, **353**, 2017, 139-149.

781 Maringanti, C., Chaubey, I. and Popp, J., Development of a multiobjective optimization tool for the selection and  
782 placement of best management practices for nonpoint source pollution control. *Water Resour. Res.*, **45**(6),  
783 2009, W06406.

784 Martin-Mikle, C.J., Beurs, K.M., Julian, J.P., Mayer, P.M., Identifying priority sites for low impact development  
785 (LID) in a mixed-use watershed. *Landsc. Urban Plan.* **140**, 2015, 29-41.

786 Miles, B. and Band, L.E., Green infrastructure stormwater management at the watershed scale: urban variable  
787 source area and watershed capacitance. *Hydrol. Process.*, **29**(9), 2015, 2268-2274.

788 Muñoz-Carpena, R., Lauvernet, C. and Carluer, N., Shallow water table effects on water, sediment, and pesticide  
789 transport in vegetative filter strips—Part 1: nonuniform infiltration and soil water redistribution. *Hydrol. Earth  
790 Syst. Sci.*, **22**(1), 2018, 53-70.

791 Natural Resources Conservation Service (NRCS), United States Department of Agriculture (USDA). Soil Survey  
792 Geographic (SSURGO) Database for Kitsap County, WA. Available online at  
793 <https://websoilsurvey.nrcs.usda.gov/>. Accessed on 1/12/2017.

794 Nemirovsky, E.M., Lee, R.S. and Welker, A.L., Vertical and lateral extent of the influence of a rain garden on the  
795 water table. *J. Irrig. Drain. Eng.*, **141**(3), 2014, 04014053.

796 Newcomer, M.E., Gurdak, J.J., Sklar, L.S. and Nanus, L., 2014. Urban recharge beneath low impact development  
797 and effects of climate variability and change. *Water Resour. Res.*, **50**(2), 1716-1734.

798 Palla, A., Gnecco, I., Hydrologic modeling of low impact development systems at the urban catchment scale. *J.  
799 Hydrol.* **528**, 2015, 361–368.

800 Perez-Pedini, C., Limbrunner, J.F. and Vogel, R.M., Optimal location of infiltration-based best management

801 practices for storm water management. *J. Water Resour. Plan. Manage.*, **131**(6), 2005, 441-448.

802 Potter, K.W., 2006. Small-scale, spatially distributed water management practices: Implications for research in  
803 the hydrologic sciences. *Water Resour. Res.*, **42**(3), W03S08.

804 Qin, H., Li, Z., Fu, G., The effects of low impact development on urban flooding under different rainfall  
805 characteristics. *J. Environ. Manag.* **129**, 2013, 577–585.

806 Regan, R.S., Niswonger, R.G., Markstrom, S.L. and Barlow, P.M., *Documentation of a restart option for the US  
807 Geological Survey coupled Groundwater and Surface-Water Flow (GSFLOW) model* (No. 6-D3). 2015, US  
808 Geological Survey.

809 Rodriguez, H.G., Popp, J., Maringanti, C. and Chaubey, I., Selection and placement of best management practices  
810 used to reduce water quality degradation in Lincoln Lake watershed. *Water Resour. Res.*, **47**(1), 2011,  
811 W01507.

812 Roseen, R.M., and Stone, R.M., 2013. Evaluation and optimization of bioretention design for nitrogen and  
813 phosphorus removal. Prepared with support from USEPA Region 1 TMDL Program, Town of Durham,  
814 Seattle Public Utilities.

815 Rossman, L.A., 2015. *Storm water management model user's manual, version 5.1* (p. 71). Cincinnati: National  
816 Risk Management Research Laboratory, Office of Research and Development, US Environmental Protection  
817 Agency.

818 Sceva, J.E., *Geology and ground-water resources of Kitsap County, Washington*. Prepared in cooperation with the  
819 State of Washington, Department of Conservation and Development, Water Resources Division. US  
820 Government Printing Office, 1957.

821 Sebti, A., Carvallo Aceves, M., Bennis, S. and Fuamba, M., Improving nonlinear optimization algorithms for BMP  
822 implementation in a combined sewer system. *J. Water Resour. Plan. Manage.*, **142**(9), 2016, 04016030.

823 Sebren, M.B., Sep 12, 2017. Email.

824 Seshadri, A., NSGA-II: A multi-objective optimization algorithm. MATLAB Central File Exchange. 2010,  
825 Retrieved 19 July, 2009.

826 Shuster, W.D., Bonta, J., Thurston, H., Warnemuende, E. and Smith, D.R., 2005. Impacts of impervious surface  
827 on watershed hydrology: A review. *Urban Water J.*, **2**(4), 263-275.

828 Sohn, W., Kim, J.H., Li, M.H., and Brown, R., 2019. The influence of climate on the effectiveness of low impact  
829 development: A systematic review. *J. Environ. Manage.*, **236**, 365-379.

830 Song, Y., 2005. Smart growth and urban development pattern: A comparative study. *Int. Reg. Sci. Rev.*, **28**(2), 239-  
831 265.

832 Stewart, R.D., Lee, J.G., Shuster, W.D. and Darner, R.A., Modelling hydrological response to a fully-monitored  
833 urban bioretention cell. *Hydrol. Process.*, **31**(26), 2017, 4626-4638.

834 Thomas, B.F. and Vogel, R.M., Impact of storm water recharge practices on Boston groundwater elevations. *J.*  
835 *Hydrol. Eng.*, **17**(8), 2011, 923-932.

836 Triadis, D. and Broadbridge, P., 2012. The Green-Ampt limit with reference to infiltration coefficients. *Water  
837 Resour. Res.*, **48**(7).

838 Trinh, D. H., and Chui. T. F. M., Assessing the hydrologic restoration of an urbanized area via integrated  
839 distributed hydrological model. *Hydrol. Earth Syst. Sci.*, **17**(12), 2013, 4789-4801.

840 Voter, C.B. and Loheide, S.P., 2018. Urban Residential Surface and Subsurface Hydrology: Synergistic Effects of  
841 Low-Impact Features at the Parcel Scale. *Water Resour. Res.*, **54**(10), 8216-8233.

842 Woods Ballard, B., Wilson, S., Udale-Clarke, H., Illman, S., Scott, T., Ashley, R. and Kellagher, R., *The SuDS  
843 Manual*; CIRIA: London, UK, 2015.

844 Xu, T., Engel, B.A., Shi, X., Leng, L., Jia, H., Shaw, L.Y. and Liu, Y., 2018. Marginal-cost-based greedy strategy  
845 (MCGS): Fast and reliable optimization of low impact development (LID) layout. *Sci. Total Environ.*, **640**,  
846 2018, 570-580.

847 Yang, Y. and Chui, T.F.M., Rapid assessment of hydrologic performance of low impact development practices  
848 under design storms. *JAWRA*, **54**(3), 2018a, 613-630.

849 Yang, Y., and Chui, T.F.M., Optimizing surface and contributing areas of bioretention cells for stormwater runoff  
850 quality and quantity management. *J. Environ. Manage.*, **206**, 2018b, 1090-1103.

851 Young, R., Zanders, J., Lieberknecht, K. and Fassman-Beck, E., A comprehensive typology for mainstreaming  
852 urban green infrastructure. *J. Hydrol.*, **519**, 2014, 2571-2583.

853 Zhang, K. and Chui, T.F.M., Evaluating hydrologic performance of bioretention cells in shallow groundwater.  
854 *Hydrol. Process.*, **31**(23), 2017, 4122-4135.

855 Zhang, K. and Chui, T.F.M., Interactions between shallow groundwater and low-impact development underdrain  
856 flow at different temporal scales. *Hydrol. Process.*, **32**(23), 2018a, 3495-3512.

857 Zhang, K. and Chui, T.F.M., A comprehensive review of spatial allocation of LID-BMP-GI practices: Strategies  
858 and optimization tools. *Sci. Total Environ.*, **621**, 2018b, 915-929.

859 Zhang, K. and Chui, T.F.M., Linking hydrological and bioecological benefits of green infrastructures across spatial  
860 scales—A literature review. *Sci. Total Environ.*, **646**, 2019, 1219-1231.

861 Zhang, K., Chui, T.F.M. and Yang, Y., Simulating the hydrological performance of low impact development in  
862 shallow groundwater via a modified SWMM. *J. Hydrol.*, **566**, 2018, 313-331.

863 Zheng, Y., Chen, S., Qin, H. and Jiao, J., 2018. Modeling the spatial and seasonal variations of groundwater head  
864 in an urbanized area under low impact development. *Water*, **10**(6), 2018, 803.

865 Zischg, J., Zeisl, P., Winkler, D., Rauch, W. and Sitzenfrei, R., On the sensitivity of geospatial Low Impact  
866 Development locations to the centralized sewer network. *Water Sci. Technol.*, **77**(7), 2018, 1851-1860.