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1 **Evaluating SWAT model performance, considering different soils data input,**  
2 **to quantify actual and future runoff susceptibility in a highly urbanized basin.**

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14

15

### **Abstract**

16 The Soil and Water Assessment Tool (SWAT) is a physical model designed to predict the  
17 hydrological processes that could characterize natural and anthropized watersheds. The model can  
18 be forced using input data of climate prediction models, soil characteristics and land use scenarios  
19 to forecast their effect on hydrological processes. In this study, the SWAT model has been applied  
20 in the Aspio basin, a small watershed, highly anthropized and characterized by a short runoff  
21 generation. Three simulations setup, named SL1, SL2 and SL3, were investigated using different  
22 soil resolution to identify the best model performance. An increase of space requirement and  
23 calibration time has been registered in conjunction with the increasing soil resolution. Among all  
24 simulations, SL1 has been chosen as the best one in describing watershed streamflow, despite it  
25 was characterized by the lower soil resolution. A map of susceptibility to runoff for the entire basin  
26 was so created reclassifying the runoff amount of four years in five classes of susceptibility, from  
27 very low to very high. Eleven sub-basins, coinciding with the main urban settlements, were

28 identified as highly susceptible to runoff generation. Considering future climate predictions, a slight  
29 increase of runoff has been forecasted during summer and autumn. The map of susceptibility  
30 successfully identified as highly prone to runoff those sub-basins where extreme flood events were  
31 yet recorded in the past, remarking the reliability of the proposed assessment and suggesting that  
32 this methodology could represent a useful tool in flood managing plan.

33

34 Keywords: Numerical model; hydrogeological risk; runoff; extreme events; risk management.

35

## 36 **1 Introduction**

37 Hydrological predictive models (HPM) represent the most recently developed tools in the field of  
38 surface water simulation. HPM are currently utilized to assess water and land management  
39 strategies in complex watersheds all over the world. In the last century, the need to define water  
40 availability and to forecast floods size and duration, together with sediments delivery has become  
41 a challenging issue for many local authorities (Wang, 2014). This has come to be very important  
42 especially for different life aspects like: i) organization of food supply, ii) security, iii) human health  
43 and iv) natural ecosystems. HPM make the users able to manipulate the system's  
44 variables/parameters, helping in the understanding of the deep interactions within variables, which  
45 are responsible of a system's complexity (Sokolowski and Banks, 2011). The knowledge of this  
46 interaction and the availability of quantitative information, that allow the understanding and the  
47 description of the hydrological cycle has become mandatory considering the recent interest on  
48 climate/land use change's effects (Chaplot, 2005). Starting from the nineteenth century, it is clear  
49 how climate variations and variability, together with changes in land use practices, have had a  
50 profound impact on basin hydrology, affecting water availability. So, it is crucial to directly  
51 quantify the climate change impacts on streamflow at regional and basin scale (Aryal et al., 2018;  
52 Bhatta et al., 2019). Sudden changes in the regime of hydro-meteorological events are the main  
53 causes of natural extreme events like droughts (Turco et al., 2017), fires (Busico et al., 2019) and  
54 floods (Kourgialas and Karatzas, 2011; Shadmehri Toosi et al., 2019) that could affect many  
55 regions of the world. Flood events have attracted the global audience and have been recognized as  
56 one of the main environmental problems, making the implementation of flood risk scenarios  
57 indispensable (Scussolini et al., 2016). Flood events are also highly influenced by the local spatial

58 and temporal characteristics of the area, and small basins can be easily subject to flash food events  
59 especially in highly urbanized areas (Tazioli et al., 2015). In this scenario, all the possibilities for  
60 flood mitigation need to be integrated into a precautionary and implementation plan. These  
61 procedures include the adaptation of land use and infrastructural planning; moreover, especially at  
62 the very beginning of flood generation, the knowledge of the runoff generation processes is  
63 mandatory to accurately implement the precaution actions (Schüler, 2007). The Soil and Water  
64 Assessment Tool (SWAT, Neitsch et al., 2000), was designed to predict the impact of agricultural  
65 management practices on water outflow, sediment, nutrient and pesticide loads for large ungauged  
66 sub-basins (Arnold et al., 1998). Regarding the hydrological processes, the major ones modelled in  
67 SWAT are: i) surface runoff, ii) soil and root zone infiltration, iii) evapotranspiration, iv) soil and  
68 snow melting contribution to runoff, and v) baseflow. SWAT has proven to be an efficient tool for  
69 simulating many hydrological processes like contaminant transport and soil erosion, and for  
70 studying the effects of climate change, land use change and water management practices in different  
71 environmental conditions (Ayana et al., 2015; Bhatta et al., 2019; Golmohammadi et al., 2017;  
72 Tasdighi et al., 2018). Recently SWAT was also involved in the generation of a flood hazard index  
73 (Shadmehri Toosi et al., 2019) using the runoff coefficient. SWAT resulted to be an effective tool  
74 for watershed management, while having uncertainties associated with conceptual parameters,  
75 physical parameters, drainage area, elevation bands and hydrological response units (HRU) (Shen  
76 et al., 2011). Careful calibration, validation and uncertainty analysis are required to achieve the best  
77 model performance. Tuo et al. (2016) evaluated SWAT performance using different precipitation  
78 input in an Alpine basin. Chaplot (2005) investigated SWAT output changes using different Digital  
79 Elevation Models (DEMs) and soil resolutions. More studies, accounting only for the DEM  
80 resolution, showed little variation in the yearly calculated runoff (Lin et al., 2013) but substantial  
81 changes in the seasonal runoff patterns (Zhang et al., 2014). To date, studies that clearly tackle the  
82 role of soil maps resolution are still lacking, except for few examples (Kumar and Merwade, 2009).  
83 The aim of this work is to simulate the runoff processes inside a small and highly urbanized basin  
84 located near Ancona, central Italy. The Aspio basin is characterized by a Mediterranean climate,  
85 with large spatial variability of both rainfall and physical characteristics, which could lead to some  
86 difficulties in simulating the runoff regime, respect to other climates (Abdelwahab et al., 2018).  
87 The SWAT performance was evaluated using three different soil maps' resolutions, and the best  
88 one was chosen to simulate runoff amount for the period 2014-2018. The choice was influenced by

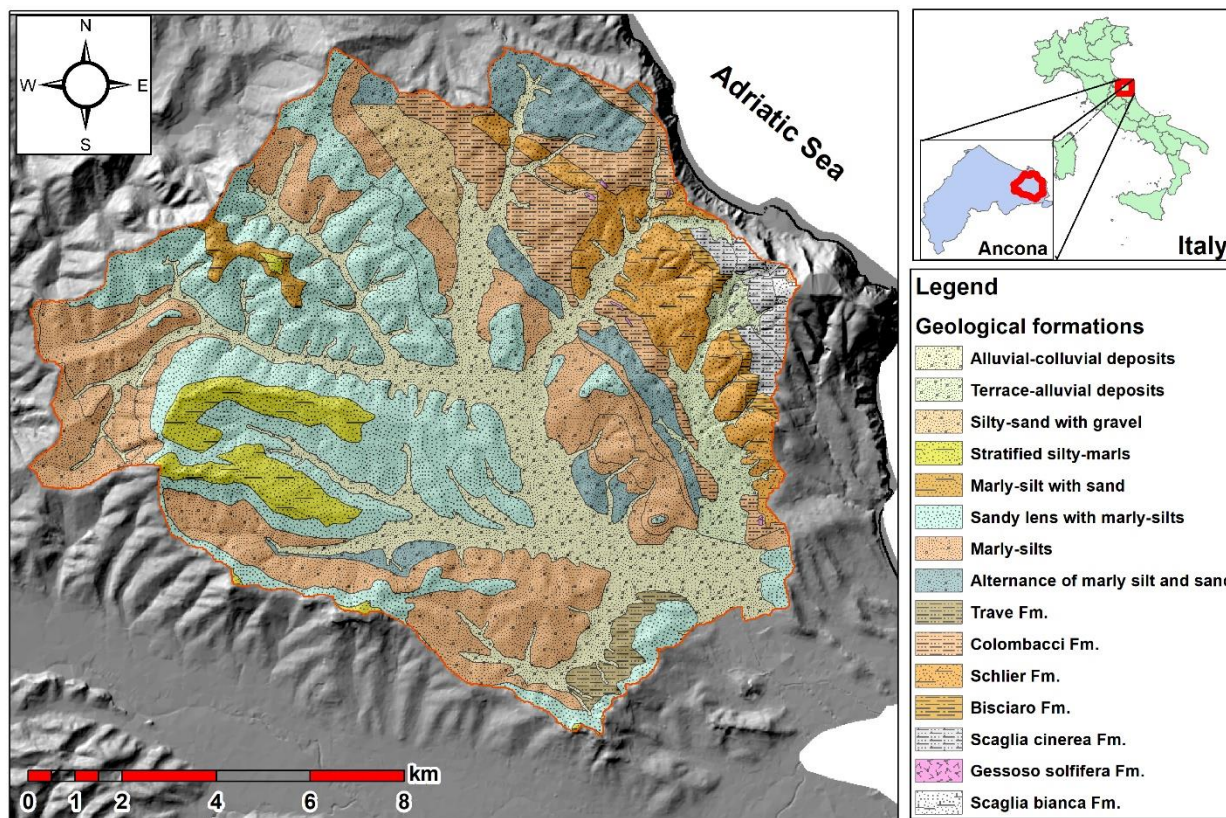
89 several factors like: i) a good fit with real data, ii) the simulation/calibration time needed to obtain  
90 reasonable results and iii) the benefit in term of CPU time and field analysis. A total susceptibility  
91 map of runoff for the whole basin was also produced accounting for the results of the four simulated  
92 years, and it was compared with the observed flooding events. A further evaluation of runoff events  
93 for the near future (2040) was also applied, using a downscaled future climate projection of the  
94 global climate model (GCM) CNRM-CM6-1 (WorldClim, 2020), to highlight how the predicted  
95 changes could positively or negatively affect the runoff phenomena.

## 96 **2 Material and methods**

### 97 **2.1 Study area**

98 The study area is the Aspio watershed, which belongs to the Marche region (Italy), in the proximity  
99 of Ancona city on the Adriatic coast (Figure 1). The Aspio watershed is characterized by the  
100 presence of small hills with smoothed shape. The Aspio river springs are located at the confluence  
101 of the Offagna, Polverigi and Gallignano ditches, and gather the surface waters of Ancona, Conero  
102 Mount and Osimo hills. The Aspio river, the main surface water course of the basin, is a tributary  
103 of the Musone river. The geological setting of the Aspio watershed consists of: i) the Meso-  
104 Cenozoic limestone sequence, ii) the Mio-Plio-Pleistocene sequence mainly made up of marly clays  
105 and marly clays with sandstone layers, and iii) the Quaternary continental deposits made up of silty  
106 clay, clayey sand and eluvial-colluvial deposits (Tazioli et al., 2015). Folds with gentle slopes and  
107 faults with Apennines and anti-Apennines direction are present in the area. Most of the hills are  
108 formed by the Mio-Plio-Pleistocene sequence that gives rise to a peculiar morphology made of  
109 gentle ridges and large depressions. The Plio-Pleistocene basin developed along the main tectonic  
110 faults and underwent a compressive phase, which was responsible for the final geomorphological  
111 evolution of the area (Mirabella et al., 2008). In the Aspio watershed the Quaternary eluvial-  
112 colluvial covers are made of sands, silty-sands and clayey silts and can reach a thickness of up to  
113 25 m. The eluvial-colluvial covers host a shallow aquifer that interacts with the Aspio river and its  
114 streams throughout the year. The Aspio watershed is characterized by a Mediterranean climate,  
115 with an average precipitation of about 800 mm/y in the valleys and 1200 mm/y in mountainous  
116 areas (Pellegrini, 2019). The land use is very heterogeneous, according to 2016 Corine Land Cover  
117 (CLC) almost 10% of the territory is occupied by urban settlements, equally divided in residential,  
118 commercial and industrial units, that are mainly located in the center of the watershed. Agricultural

119 areas area dominated by cereals plantation and occupy more than 60% of the basin, and are directly  
120 connected with urban areas. Forests represent less than 2% of the entire watershed.



121  
122 Figure 1: Location and geology of the Aspicio Watershed.

123  
124 Regarding the land use changes inside the Aspicio basin, analyzing the land cover maps from the  
125 CLC database for the years 2006, 2012 and 2018, no significative changes were recorded trough  
126 years. Table S1 shows the different extension of land cover classes based on Level 1 of CLC  
127 classification. From 2006 to 2012, very small changes were registered, namely an increase of  
128 artificial and forest areas was identified at the expenses of agricultural fields. From 2012 to 2018  
129 instead, no variation has been observed for all the three land-use classes.

## 130 131 2.2 Soil and Water Assessment Tool (SWAT) Model

132 The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998; Arnold et al., 2012) was  
133 initially developed by the United States Department of Agriculture (USDA) to simulate the effects

134 of land management practices on the hydrological cycle. SWAT is a physically based and semi-  
135 distributed hydrological model able to operate on a different timescale (daily, monthly and annual),  
136 generally designed to model and predict continuous long-time runoff, sediment and agricultural  
137 chemical yields with watershed and river-basin scale input data. The model is constructed on the  
138 concept of hydrologic response units (HRU). A watershed is divided into multiple sub-watersheds,  
139 which are further subdivided into HRU, that in turn are portions of a territory characterized by  
140 unique land-use/management/soil attributes. The outputs of runoff, sediment, and nutrient loadings  
141 from each HRU are generated separately using the input of weather, soil properties, topography,  
142 vegetation, and land management practices, and finally summarized to determine the total loadings  
143 from each sub-basin. Precisely, SWAT divides the hydrological processes into two different steps:  
144 i) land phase, where the input of water, sediment, nutrients and pesticides are calculated in the main  
145 channel and inside each sub-basin (Cibin et al., 2010), and ii) a routing phase, that connects all sub-  
146 basins by means of the main channel and simulates the movement of water and sediment to the  
147 basin outlet. SWAT offers two methodologies for the runoff calculation: i) a modified version of  
148 the curve number method (USDA-SCS, 1972) and ii) the Green–Ampt infiltration method, while  
149 the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1995) is applied to predict  
150 sediment generation.

151

### 152 **2.3 Model set-up**

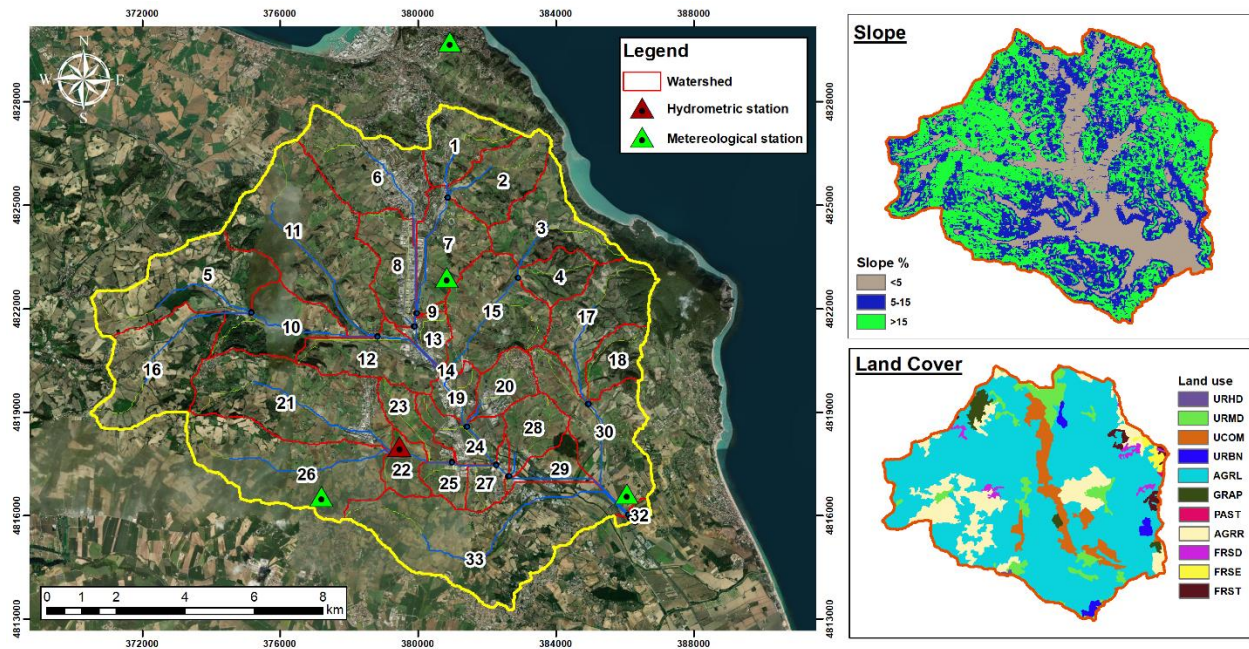
153 The SWAT model for the Aspio basin has been built using information concerning morphology,  
154 land cover, soil properties and climate data. The ArcSWAT 2012 version on ArcGIS 10.2 platform  
155 has been used for the elaboration in this work. In Table S2 all the sources of the utilized data are  
156 listed. For the realization of a regular SWAT simulation three main steps are needed. First, using  
157 the “Watershed automatic delimitation” all the topographical inputs were calculated starting from  
158 a 20 m resolution Digital Elevation Model (DEM) to define the watershed features like boundaries,  
159 river network, sub-basins, and to derive slope-related parameters. For the Aspio basin, an area of  
160 155 km<sup>2</sup> has been divided in 33 sub-basins (Figure 2) with a minimum and maximum elevation of  
161 8 m and 540 m above sea level (a.s.l.), respectively. The second phase includes the HRU definition,  
162 intersecting data of slope, land cover and soil property information. The slope ranges were  
163 established using the 20 m resolution DEM and classified in 3 classes: less than 5°, between 5° and



164 15°, and more than 15°. As no significative changes in land use were recorded in the last 20 years,  
165 the CLC map for 2018 has been used for HRU delimitation. Eleven land covers were identified  
166 (mainly industrial, residential, agricultural and agro-forestry) and homogenized with SWAT2012  
167 crop's default database. Regarding soils' properties, SWAT requires the information about soil  
168 hydraulic conductivity (Ks), soil water content, texture, percentage of organic carbon, soil albedo  
169 ad more. For this study three different soil maps have been used (Figure S1), inasmuch, the soil  
170 properties represent one of the three information needed in the construction of the HRU. The first  
171 simulation (SL1) utilized the soil information derived from the Digital Soil World Map (DSMW;  
172 FAO, 2007) with a scale of 1:5 million. According to FAO DSMW classification (Figure S1a), the  
173 Aspio basin is characterized by one soil category (Eutric Gleysol) with a Ks of 7.32 mm/h, a soil  
174 bulk density (BD) of 1.3 g/cm<sup>3</sup> and an available water capacity (AWC) of 0.164 mm H<sub>2</sub>O/mm of  
175 soil. For the second simulation (SL2) a more detailed soil map was constructed based on the  
176 geologic characteristics of the study area with a scale of 1:10000. In this case the classification was  
177 done using at least 3 Ks values of the topsoils (Figure S1b) measured with a double ring  
178 infiltrometer in the respective geological formations, while all the other parameters have been  
179 integrated using the SWAT soil's default database selecting the soil type and texture. Thirteen soil  
180 formations (Figure S1c) were identified with a Ks ranging from 0.35 to 324 mm/h, an average BD  
181 of 1.5 g/cm<sup>3</sup> and AWC values from 0.073 to 0.175. The last simulation (SL3) was constructed using  
182 only those soil units (Figure S1b) with the maximum extension among the thirteen previously  
183 utilized for SL2. In this case three main soil units have been chosen as representative of the entire  
184 basin. Soil data for SL2 and SL3 come from previous analyses realized by Università Politecnica  
185 delle Marche (Mattioli, 2012) and are shown in Table S3 together with soil data for SL1. Parameters  
186 like Ks, clay, silt and sand content have been measured in the field while the values of AWC and  
187 BD were adjusted using a hydraulic property calculator and integrated with the default SWAT2012  
188 input database's values. For all the three simulation 33 sub-basins were created and further divided  
189 into HRU, using a threshold of less than 10% for land use, for soil type, and slope. The HRU  
190 threshold was employed to further discretize each sub-basin, especially for SL2 and SL3 where a  
191 great heterogeneity in land use, soil and slope was found (Her et al., 2015). The last necessary input  
192 are the meteorological data. SWAT asks for daily variables of precipitation, temperature, relative  
193 humidity, solar energy, and wind speed. Among these parameters, precipitation is directly involved  
194 in the runoff calculation, and together with temperatures, wind speed, humidity and solar radiation,

195 is utilized for the calculation of the evapotranspiration. Depending to the data availability three  
196 methodology are provided for the calculation of potential evapotranspiration (Aschonitis et al.,  
197 2017): i) Priestly-Taylor, ii) Penman/Monteith and iii) Hargreaves. The software also offers a  
198 weather generator tool to fill missing data for certain periods and furthermore it allows for the  
199 simulation of all climate variables, if an historical database related to the watershed is available. In  
200 this case the Hargreaves method has been adopted for the estimation of the evapotranspiration rates  
201 on the catchment for all the three simulations, instead of using the weather simulation tool according  
202 to available climate data. Daily precipitation together with maximum and minimum temperature  
203 data, coming from four meteorological stations (Osimo, Ancona, Baraccola, Svarchi) located inside  
204 the Aspio basin, have been used for the simulations. Such data are part of Marche Region  
205 Meteorological-Hydrological Information System (SIRMIP, 2020). To examine the future trend of  
206 runoff generation the values of predicted temperatures and precipitations coming from the  
207 WorldClim database for the period 2021–2040 have been utilized for a post validation SWAT run.  
208 The selected database for the period 2021–2040 is a Coupled Model Intercomparison Project  
209 (CMIP6) downscaled future climate projection of the global climate model (GCM) CNRM-CM6-  
210 1 with the Shared Socio-economic Pathway (SSP) 2-4,5, at a spatial resolution of 2.5 minutes  
211 (WorldClim, 2020). Generally for Mediterranean area an average increase of 1.5–2.0° C of  
212 temperature is predicted, especially in the summer period (Giorgi and Lionello, 2008) together with  
213 a decrease of precipitation with a marked seasonal regime: a decrease of around 30-40 % in  
214 precipitation during the summer period and an increase of 25-20% during the winter period  
215 (Bucchignani et al., 2016; Mastrocicco et al., 2019). Also, in this case the Hargreaves method has  
216 been applied for PET calculation accordingly to data availability.

217



218

219 Figure 2: SWAT model setup for the Aspicio basin containing watershed subdivision, slope classes  
 220 and land use dominance.

221

## 222 2.4 Calibration and validation

223 The main requirements for a model evaluation are: i) measuring the reliability of the criteria and ii)  
 224 the robustness of the methodology. This is investigated through a calibration and validation  
 225 procedure. The auto-calibration tool was used as calibration and validation technique, via the  
 226 standalone program SWAT-CUP using the Sequential Uncertainty Fitting version 2 (SUFI-2)  
 227 algorithm (Abbaspour, 2015). SUFI-2 is well known to estimate both parameters and model  
 228 uncertainties in hydrological models (Abbaspour, 2015). Within SWAT-CUP the user can select  
 229 the most sensitive parameters that could influence the observed outputs (e.g. streamflow,  
 230 sediment/chemical yield) and choose a range of variation (e.g.  $\pm 25\%$  of the initial value). During  
 231 the calibration procedure the algorithm tries different combination of parameters within their new  
 232 ranges and calculates the effect on the fitting between observed and simulated variables. Finally,  
 233 the results obtained from the calibration/validation procedure are evaluated computing different  
 234 statistical indices. In the present study the robustness of the applied methodology was defined by  
 235 means of three indices: coefficient of determination ( $R^2$ ), Nash-Sutcliffe efficiency (NSE) and  
 236 percent of bias (PBIAS). The indices are calculated following the formulas below:

237

$$R^2 = \left( \frac{\sum_{i=1}^n (K_{predicted} - \bar{K}_{predicted})(K_{measured} - \bar{K}_{measured})}{\sqrt{\sum_{i=1}^n (K_{predicted} - \bar{K}_{predicted})^2 * \sum_{i=1}^n (K_{measured} - \bar{K}_{measured})^2}} \right)^2 \quad (1)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (K_{predicted} - K_{measured})^2}{\sum_{i=1}^n (K_{predicted} - \bar{K}_{predicted})^2} \quad (2)$$

$$PBIAS = \left( \frac{\sum_{i=1}^n (K_{measured} - K_{predicted})}{\sum_{i=1}^n K_{predicted}} \right) * 100 \quad (3)$$

241

242 where  $K_{predicted}$  is the value predicted from the model,  $\bar{K}_{predicted}$  is the average value between the  
 243 predicted values.  $K_{measured}$  is the value measured in field and  $\bar{K}_{measured}$  is the average value between  
 244 the real data.

245 According to Moriasi et al. (2007), the optimal thresholds for the three statistical indices for an  
 246 acceptable streamflow simulation are  $R^2 \geq 0.50$ ,  $NSE \geq 0.50$  and  $PBIAS \pm 25\%$ .

247 Simulations have been calibrated and validated using daily streamflow data coming from the  
 248 Scaricalasino hydrometric station (Figure 2) for the period 2015-2018. Real data were compared  
 249 with the streamflow outlet of sub-basin 24. Calibration was performed using daily data for the  
 250 period 2015-2016 and validation was performed for the period 2017-2018.

251

### 252 3 Results and Discussion

253 One of the first result identified, comparing the HRU formation for SL1, SL2 and SL3 was the  
 254 increase in complexity of the model together with a rise of computational resources needed in terms  
 255 of Gigabyte occupied. While SL1 recognized 351 HRU, SL2 and SL3 identified 683 and 1029  
 256 HRU, respectively. It is clear how the different spatial discretization of soil types for the three  
 257 simulations directly influenced the number of HRU together with model weight and complexity.  
 258 After the set-up procedure, all the three models were run for the period 2010-2018 using the first  
 259 four years as warm-up period.

260

### 261 3.1 Sensitivity analysis and model performance evaluation

262 As described in paragraph 2.4, the SWAT-CUP program with SUFI-2 algorithm has been used for  
 263 the calibration/validation procure of SL1, SL2 and SL3. The calibration parameters have been  
 264 chosen trough literature review. According to Malagò et al. (2015), Khelifa et al. (2017) and Chen  
 265 et al. (2019) eleven parameters (Table 1) were identified as the most relevant in affecting the stream-  
 266 flow simulation. The NSE index was chosen as optimization function for the calibration procedure  
 267 and, together with PBIAS and  $R^2$ , it was used in this study to check model performance, following  
 268 the boundary value suggested by Moriasi et al. (2007). The calibration procedure was carried out  
 269 for SL1, SL2 and SL3 retaining the same initial parameters setup. A total of 2000 runs of  
 270 calibration, divided in four interactions of 500 runs each, were performed for each simulation. The  
 271 first interaction was done using the initial boundary (Min and Max columns in Table 1) of the  
 272 chosen eleven parameters as suggested by Abbaspour (2015). The increasing number of HRU from  
 273 SL1 to SL3 and SL2, together with the model complexity, was accompanied by a general increase  
 274 of time needed for successfully run a calibration procedure.

275

276 **Table 1:** List of parameters used for model calibration.

Parameter Name	Description	Method	Min Value	Max Value
<b>CH_N2.rte</b>	Main channel Manning number	Replace	0	0.3
<b>CH_K2.rte</b>	Effective hydraulic conductivity	Replace	5	130
<b>ALPHA_BF.gw</b>	Baseflow alpha factor	Replace	0	1
<b>SOL_AWC.sol</b>	Available water capacity of the soil	Relative	-0.2	0.4
<b>ESCO.hru</b>	Soil evaporation compensation factor	Replace	0.8	1
<b>SOL_BD.sol</b>	Moist Bulk density	Relative	-0.5	0.6
<b>GW_REVAP.gw</b>	Groundwater evaporation coefficient	Replace	0	0.2
<b>ALPHA_BNK.rte</b>	Baseflow alpha factor for bank storage	Replace	0	1
<b>SOL_K.sol</b>	Saturated hydraulic conductivity	Relative	-0.8	0.8
<b>GW_DELAY.gw</b>	Groundwater delay time	Replace	30	450
<b>CN2.rte</b>	Initial SCS curve number	Relative	0	0.3

277

278 According to Rouholahnejad et al. (2012) the processing time of these models can be rather long,  
 279 not allowing proper model calibration and uncertainty analysis. For SL1, SL2, and SL3,  
 280 maintaining the same number of parameters to be calibrated, an increase in time was recorded with  
 281 increasing number of HRU. For 100 simulations of SUFI-2 performed on a commercial 3.60 GHz  
 282 CPU with 12 GB RAM, SL1, SL2 and SL3 took 1 hour, 2 hours and 30 minutes, and 1 hour and 55

283 minutes processing time, respectively. SWAT-CUP allows to perform a local or a global sensitivity  
 284 analysis: i) the local sensitivity demonstrates the sensitivity of a single variable to the changes if all  
 285 other parameters values are kept constant, while ii) the global sensitivity analysis explores all the  
 286 possible input combination between parameters. So, the utilization of the global sensitivity  
 287 promotes a multilinear regression of the entire input space, giving an estimation of the overall effect  
 288 of all the inputs or their combined effect on the variation of output based on many models runs  
 289 (Song et al., 2015). In this work the global sensitivity analysis has been applied as it was found to  
 290 be the most recommended for hydrogeological processes from many authors (Baroni and Tarantola,  
 291 2014; Rosolem et al., 2012) The results of the sensitivity analysis for SL1, SL2 and SL3 are shown  
 292 in Table 2.

293

294 **Table 2:** Sensitivity analysis results and calibrated values for SL1, SL2, and SL3. For parameters  
 295 description please refer to Table 1. Values in bold are the most sensitive parameters.

SENSITIVITY	SL1	SL2	SL3	SL1	SL2	SL3
Parameter Name	P-Value	P-Value	P-Value	Calibrated value	Calibrated value	Calibrated value
CN2.rte	<b>0.00</b>	<b>0.00</b>	<b>0.00</b>	-0.35	-0.41	-0.35
CH_K2.rte	<b>0.00</b>	<b>0.00</b>	<b>0.00</b>	21.2	26.50	27.50
ALPHA_BF.gw	<b>0.00</b>	<b>0.28</b>	<b>0.00</b>	0.00	0.05	0.00
SOL_AWC.sol	<b>0.00</b>	0.65	<b>0.00</b>	0.14	0.00	0.25
ESCO.hru	<b>0.01</b>	0.68	<b>0.00</b>	0.82	0.84	0.84
SOL_BD.sol	<b>0.02</b>	<b>0.16</b>	<b>0.03</b>	-0.41	-0.25	-0.36
GW_REVAP.gw	<b>0.28</b>	<b>0.24</b>	0.80	0.14	0.15	0.14
ALPHA_BNK.rte	<b>0.43</b>	0.92	<b>0.30</b>	0.06	0.00	0.05
SOL_K.sol	0.65	<b>0.01</b>	<b>0.04</b>	-0.28	-0.28	-0.45
GW_DELAY.gw	0.88	<b>0.28</b>	0.90	222	200.0	255.0
CH_N2.rte	0.98	<b>0.17</b>	0.93	0.15	0.13	0.17

296

297 Among the eleven chosen parameters, eight sensitive ones have been detected to be important in  
 298 regulating the streamflow generation for all the simulations (bold values in Table 2). Each  
 299 simulation differs for the type of sensitive parameter and for its relative weight: i) for SL1, SCS  
 300 runoff curve (CN2) and effective hydraulic conductivity for the main channel (CH\_K2) together  
 301 with some soil characteristics like soil water content (SOL\_AWC), bulk density (SOL\_BD), soil  
 302 evaporation factor and baseflow factor (ALPHA\_BF) were identified as the factors that produced  
 303 the higher impact on streamflow simulation, ii) in SL2, besides CH\_N2, CH\_K2 and ALPHA\_BF  
 304 also soil hydraulic conductivity (SOL\_K), groundwater delay time (GW\_DELAY), and Manning's

305 value (CH\_N2) were detected as sensitive parameters, and iii) for SL3 the result is almost the same  
 306 as for SL1, with the only introduction of SOL\_K. These results indicate that the greater number of  
 307 soil units are considered, the more importance is gained by the hydraulic conductivity (SOL\_K) in  
 308 the streamflow/runoff generation. So, after the first interaction, the following ones were started  
 309 using only the eight sensitive factors for SL1, SL2 and SL3 to obtain the fitted parameters' values  
 310 (Table 2). The final calibration performances of the three models (SL1, SL2 and SL3) were assessed  
 311 using three statistical indices and are reported in Table 3.

312

313 **Table 3:** Performance analysis of the SWAT model in simulating streamflow during the calibration  
 314 procedure. Values in bold are above the optimal thresholds defined by Moriasi et al. (2007).

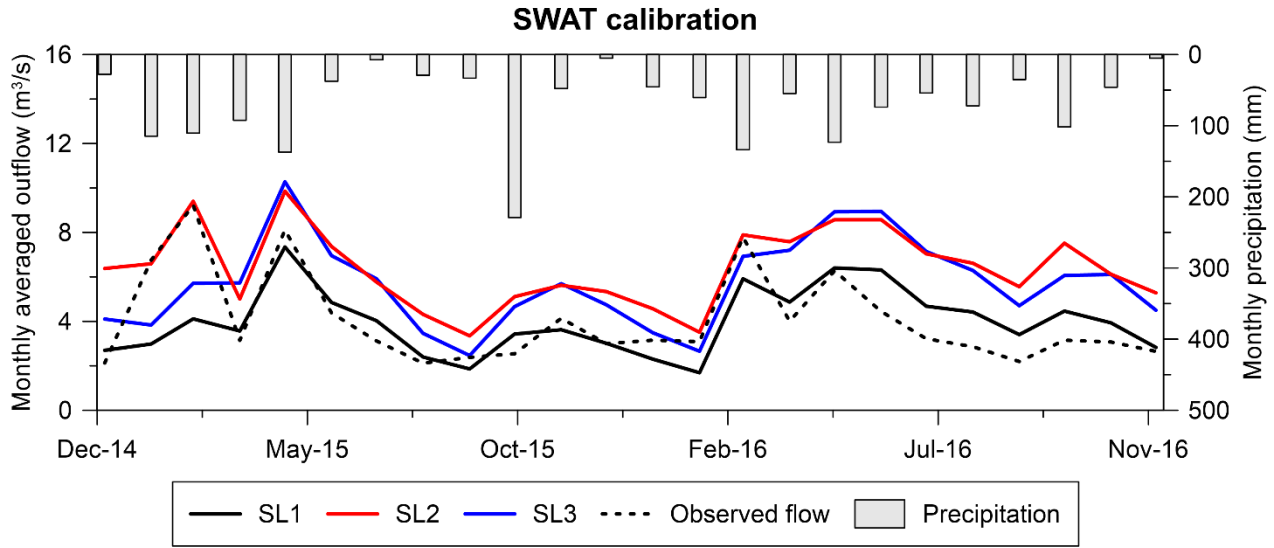
Statistical parameters	Moriasi et al. (2007)	SL1	SL2	SL3
Coefficient of determination ( $R^2$ )	$\geq 0.50$	<b>0.76</b>	<b>0.65</b>	<b>0.71</b>
Nash-Sutcliffe efficiency (NSE)	$\geq 0.50$	<b>0.65</b>	0.36	0.42
Percent bias in volume (PBIAS)	$\pm 25$	<b>6.1</b>	-56.1	-32.9
CPU time for 100 runs (minute)		<b>60 min</b>	150 min	115 min

315

316 As shown in Table 3, SL1 is the only one whose values are within the range of acceptability for the  
 317 three statistical indicators. SL1 shows a high  $R^2$  of 0.76 and a good NS value of 0.65, nevertheless,  
 318 the positive value of PBIAS (6.1%) indicates a little underestimation of the daily streamflow.  
 319 Regarding SL2 and SL3, two of the three statistical indices (NSE and PBIAS) are outside the range  
 320 qualifying an acceptable performance and moreover, both SL2 and SL3 greatly overestimate the  
 321 streamflow (negative PBIAS). Figure 3 shows a comparison of the three model simulations with  
 322 real data using monthly values. Among the models, SL1 shows a good monthly correspondence  
 323 with real data and a comparable general trend. On the other hand, SL2 and SL3 while showing a  
 324 good general trend, overestimate the streamflow values 3 to 4 times. The Figure S2, S3 and S4  
 325 represent the main water balance components for the three simulations. The main difference  
 326 concerns the evapotranspiration that is maximal in SL1 and is reduced in the other two scenarios.  
 327 The recharge to the shallow aquifer slightly reduces in SL2 and SL3 compared to SL1, while the  
 328 lateral flow in SL2 and SL3 increases, and the runoff for SL2 and SL3 is three time higher (150  
 329 mm) than SL1 (41 mm). In general, in SL2 (264 mm) and SL3 (255 mm) a higher amount of water  
 330 returns to the streams (runoff, later flow and return flow) respect to SL1 (148 mm) explaining the

331 streamflow overestimation shown in Figure 3. Moreover, ordering the simulations according to the  
332 number of soil units employed, a general linear decrease of the statistical indices from SL1 (one  
333 soil) to SL3 (three soils) and finally to SL2 (thirteen soils) is recorded. This finding agrees with  
334 Chaplot (2005), which stated that not always the extra cost and labor to obtain the greatest precision  
335 in input, like soil characteristics, bring to more accurate predictions. So, considering that SL2 and  
336 SL3 despite involving more detailed information have showed the worse simulation results, SL1  
337 has been chosen as reference simulation for the validation procedure. It is also true that SL2 and  
338 SL3 showed a good  $R^2$  with real data, following the same trend, but with higher predicted volume.  
339 It is surely possible that with further modifications of some soil parameters, together with more  
340 calibration runs, those simulations could bring to better results but, at the same time, this could be  
341 highly time consuming and not cost effective. So, there are several main reasons why the SL1 has  
342 been chosen: i) open access database has been used (no field analysis needed), ii) less space  
343 requirement and iii) an acceptable simulation time to achieve satisfactory results. The model's  
344 performance for the calibration and validation periods are represented in Figure 4. Both calibration  
345 and validation are satisfactory with NSE and  $R^2 \geq 0.50$  and PBIAS  $\pm 25\%$ . For the validation  
346 procedure all the three statistical indices are in the range of a "good" calibration with a  $R^2$  of 0.80,  
347 an NSE of 0.60 and a PBIAS of -15.35%. The streamflow representation in Figure 4 confirms a  
348 little underestimation for the calibration (positive PBIAS) and an overestimation for the validation  
349 procedure (negative PBIAS), but in any case within the acceptable range (PBIAS  $\pm 25\%$ ). In general,  
350 SL1 shows a satisfactory model performance especially in simulating the highest peaks of  
351 streamflow.

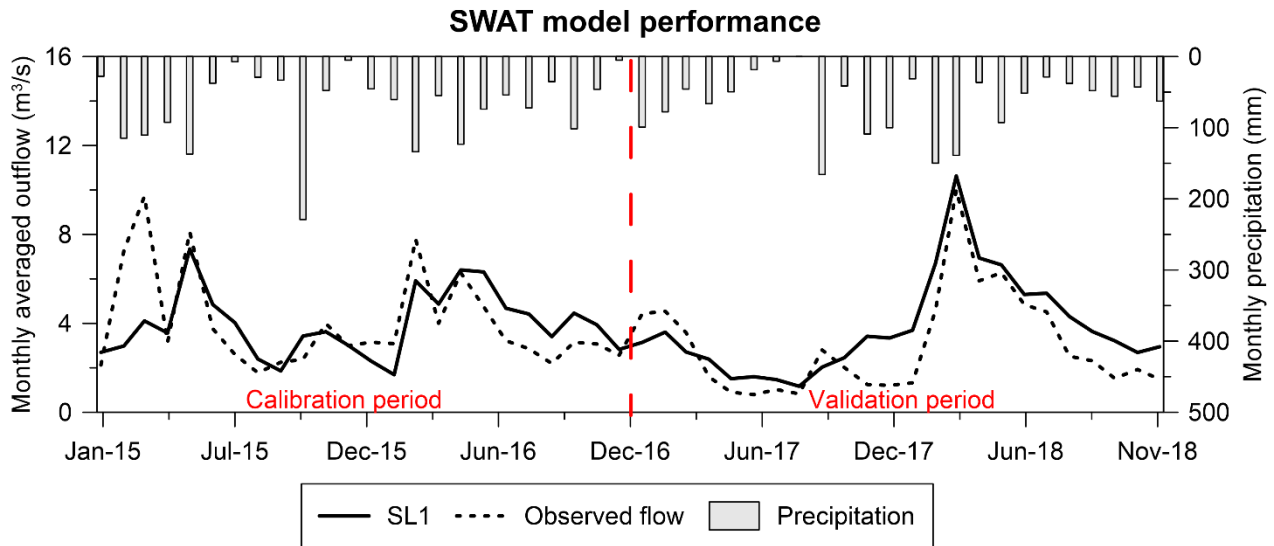




352

353 Figure 3: SWAT streamflow simulation for SL1, SL2 and SL3 after calibration procedure.

354



355

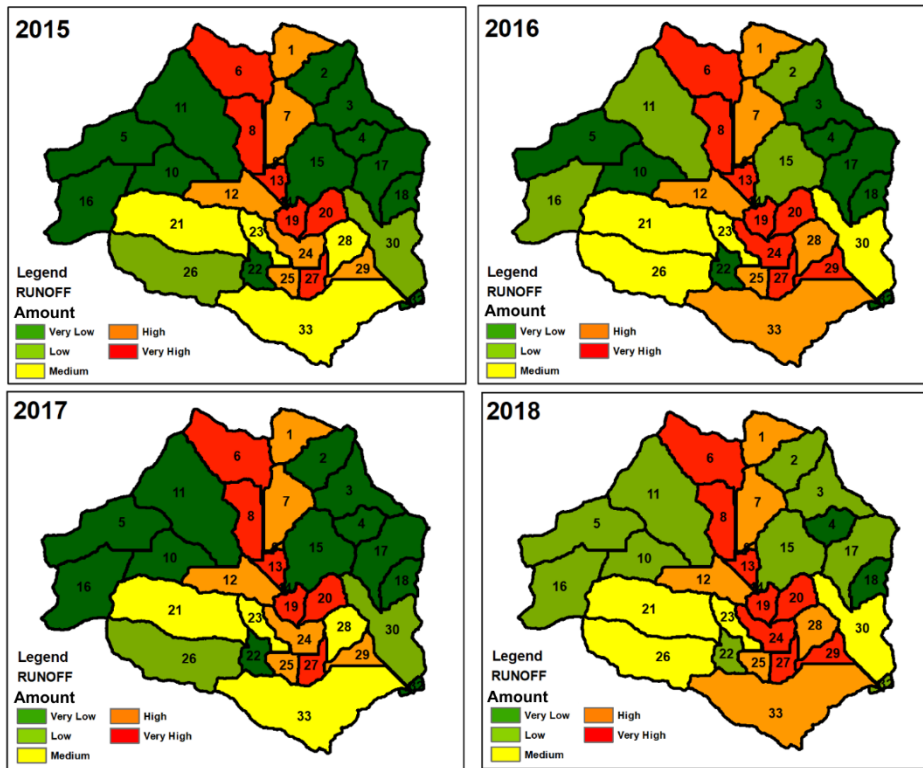
356 Figure 4: SWAT calibration/validation for SL1.

357

358 **3.3 SWAT runoff generation areas and total runoff susceptibility**

359 Following the calibration/validation procedure, the SWAT model was run for the period 2015-2018  
 360 in the entire basin. Among the available model's outputs, it was chosen to integrate the SWAT  
 361 output SURQ (Surface runoff contribution to streamflow during time step, mm H<sub>2</sub>O) for the 4 years

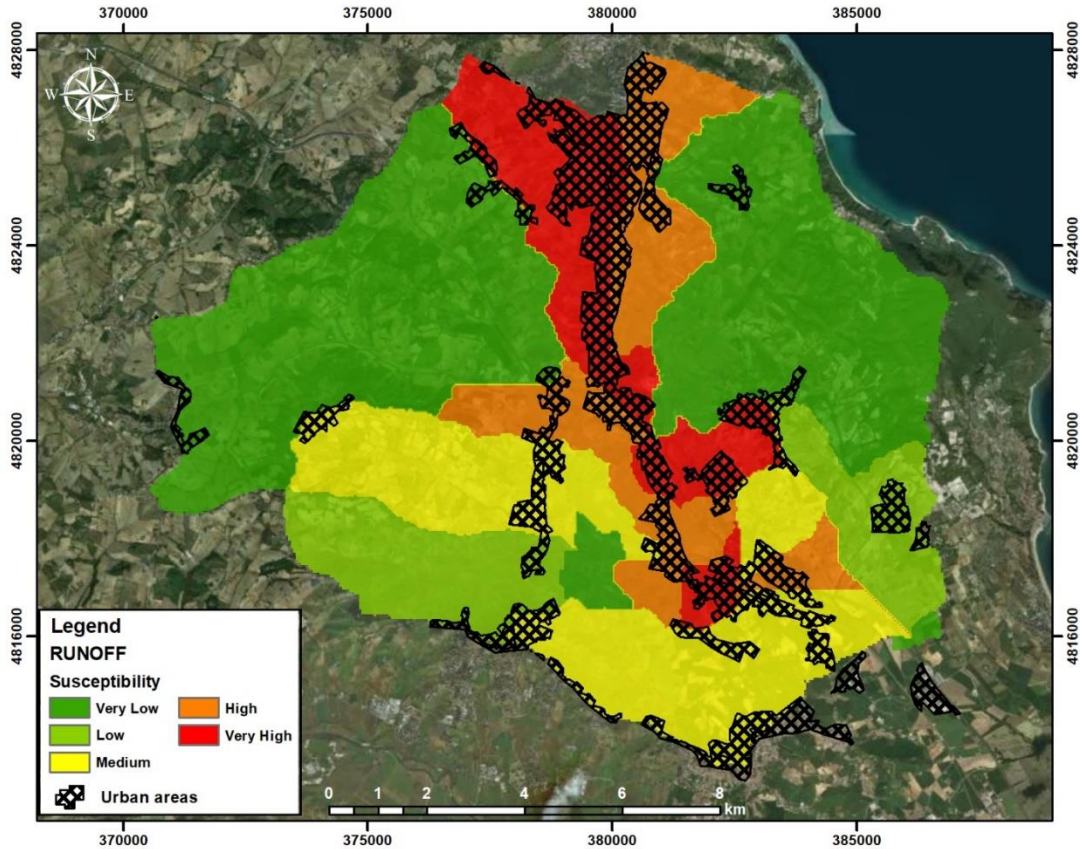
362 of simulation. This choice depends to some characteristics of the study area where a short runoff  
363 time occurs, that can lead to high flood risks especially in small basin (Pappenberger et al., 2005).  
364 The runoff values for the 33 sub-basins range between a minimum of 3 mm/y to over 250 mm/y in  
365 the 4 simulated years. Figure 5 shows a spatial representation of runoff amounts for the Aspicio basin  
366 in the analyzed period. The values of runoff were here reclassified in 5 qualitative classes from very  
367 low to very high using the geometrical interval, that is the most used classification interval for the  
368 spatial representation of many environmental parameters (Barzegar et al., 2019; Huan et al., 2012;  
369 Kazakis et al., 2019). Looking at the maps (Figure 5) it is possible to appreciate how, despite the  
370 change in meteorological condition within the analyzed years, some sub-basins seem to be always  
371 characterized by higher amount of runoff compared to others. The sub-basins 1, 6, 7, 8, 12, 13, 19,  
372 20, 24, 27 and 28 are always characterized by high and very high amount of runoff. In particular,  
373 sub-basin 24 generates less runoff for 2015 and 2017 respect to 2016 and 2018. In these two latter  
374 years, even thou cumulative precipitation was smaller compared to 2015 and 2017, extreme rain  
375 fall events have been registered which lead to an increase in the annual runoff value. Considering  
376 the four simulated years, a total susceptibility map to runoff events has been produced. This map  
377 allows to identify the area that, independently from meteorological condition, could generate high  
378 amount of runoff. To realize the final map, each one of the yearly maps have been reclassified from  
379 1 (very low) to 5 (very high) according to runoff values. Finally, a linear combination of the yearly  
380 map divided for the number of years involved has been produced using the raster calculator tool in  
381 ArcGIS 10.2. The total susceptibility map to runoff production is shown in Figure 6. The sub-basins  
382 characterized by higher runoff rate remained the same previously mentioned and are mainly  
383 concentrated in the center of the basin, while the ones with lower production of runoff spread to the  
384 East and West boundaries. The classification follows the spatial heterogeneity of land-use. The map  
385 shows how the areas susceptible to generate high runoff amount follow the distribution of the  
386 urban/commercial areas, while the agricultural and forested areas, despite the higher slope, generate  
387 less runoff. The susceptibility of urban areas to runoff is generally higher than agricultural and  
388 forestry ones (Ferreira et al., 2012, 2015). In this situation, the runoff could be up to 5 times higher  
389 in a developed urban area compared to a forestry territory where it is reduced by evapotranspiration  
390 and infiltration. The same happens also if the agricultural landscape is developed into an urban area,  
391 here, the runoff tends to increase even more due to an increasing imperviousness of the surface  
392 (Branger et al., 2013; Dietz and Clausen, 2008).



393

394 Figure 5: Qualitative representation of the runoff amounts for the four simulated years.

395



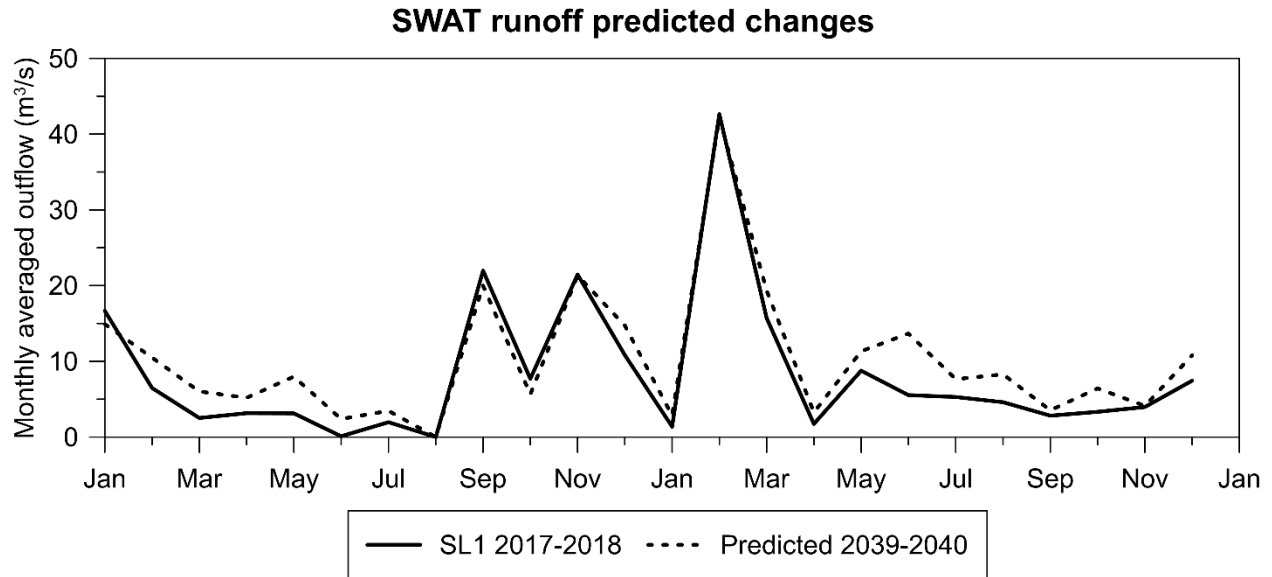
396

397 Figure 6: Total runoff susceptibility map for the Aspicio basin.

398

399 Another concern for the urban area is represented by the manmade drainage system that becomes  
 400 the only way of discharge. Despite of the naturally meandering streams and rivers, channels are  
 401 normally straight, and the resistance of concrete channels is normally lower than that of natural  
 402 streams and rivers. These could bring to shorten the runoff time and increase the peak flow  
 403 downstream (Bedient et al., 2012) with a consequently higher flood risk. To account for the possible  
 404 runoff changes due to land use variations, a series of model scenarios were produced using different  
 405 CLC (2006, 2012, 2018) without any significant change. Even producing a piecewise SWAT  
 406 simulation using CLC 2006 for the years from 2010 to 2012, CLC 2012 from 2012 to 2018 and  
 407 CLC 2018 for 2018, no changes in the runoff outputs were detected. This confirms that inside a  
 408 basin where no significative changes in land use occur, the low and high peaks of runoff trough  
 409 years are entirely dependent on climate variability. While, if land use changes are large (e.g. >40%)  
 410 during the simulated period, calculated monthly and daily runoff can considerably be affected (Lin

411 et al., 2015). Following this assumption, a further runoff prediction considering world climate  
412 prediction under SSP2-4.5 scenario is shown. In this case the daily precipitation and temperature  
413 for all the four meteorological stations were modified considering the SSP2-4.5 scenario prediction,  
414 while maintaining unchanged the land use distribution. For the precipitations pattern, an overall  
415 20% of decrease is predicted for 2040, but the decrease will not be regularly distributed during the  
416 year. The decreasing trend is also confirmed from a regional study on historical climate data,  
417 together with an increase of extreme events like storms and droughts, which can further promote  
418 the occurrence of calamitous events (Gentilucci et al., 2020). Thus, a decrease of 35% in  
419 precipitation has been applied to the months of January, February and March; while a decrease of  
420 20% has been applied to May, November and December and an increase of 25% to June, July,  
421 August and September. The months of April and October have not undergone any change. The  
422 decrease/increase rate has been decided considering the average monthly precipitation values for  
423 the period 2020-2040 using the CNRM-CM6-1 Earth system model provided in Figure S5. Using  
424 the same approach an average of 1.5° C has been added to minimum and maximum temperatures  
425 for evapotranspiration calculation. Considering these changes, a new SWAT run was applied for  
426 the period 2036-2040 using the same calibrated values of SL1. Runoff for sub-basin 24 has been  
427 chosen for runoff comparison since it belongs to a high runoff susceptibility class. Figure 7 shows  
428 the comparison of runoff for a period of two years, 2017-2018 for the actual situation and 2039-  
429 2040 for the future. Comparing the predicted data of runoff simulated by SWAT, a general increase  
430 has been predicted for the years 2039-2040, despite the annual precipitation decrease. The runoff  
431 switches from 199 mm in 2017-2018 to 245 mm in 2039-2040. Looking at Figure 7, the same  
432 amount of runoff is recorded in winter and spring (December, January, February, March and April)  
433 and a slight increase during summer (especially for May, June and July). This finding suggests that  
434 even those months which are generally considered safe have become critical, since the more  
435 abundant precipitation in such months, together with the increase of the extreme events, could  
436 increase the susceptibility to extreme flood events.



437

438 Figure 7: Comparison of the monthly runoff calculated (2017-2018) and predicted (2039-2040)  
 439 for sub-basin 24 for the SL1.

440

441 Finally, the analysis of the Civil Protection report on the flooding event occurred on the 16<sup>th</sup> of  
 442 September 2006 (Civil Protection Marche Region, 2006) highlighted that the urban areas flooded  
 443 during that extreme event (Figure S6), located between Aspio Terme and Osimo Stazione villages,  
 444 are estimated as high and very high zones of runoff susceptibility in the total runoff susceptibility  
 445 map for the Aspio basin shown in Figure 6. Moreover, a second and less important flooding event  
 446 was recorded between the 9<sup>th</sup> and 10<sup>th</sup> of March 2010 (Civil Protection Marche Region, 2010) where  
 447 numerous distributed inundations occurred within the lower portion of the Aspio basin, in  
 448 coincidence with the high and very high zones of runoff susceptibility. This further contributes to  
 449 confirm the reliability of the applied methodology, making it a useful tool for local authorities in  
 450 preventing flood events inside urban areas.

451

## 452 4 Conclusions

453 SWAT model performance in simulating the hydrogeological regime has been evaluated for the  
 454 Aspio basin, near Ancona city (Italy) using different soil configurations. Three soil maps were  
 455 employed: i) FAO DWSM, ii) soil information derived from local geology, and iii) a soil map

456 obtained considering only the three main units (higher extension) identified from local geology.  
457 The results of the calibration procedure indicate a worsening of the performance if an increasing  
458 number of soil units is considered. Within the three simulations, only SL1 showed a good  
459 performance and was so further utilized in the validation procedure. The final statistical indices for  
460 SL1 confirmed that this simulation is the best one for the simulation of the daily streamflow for the  
461 Aspio basin. Furthermore, the model's output of yearly runoff was integrated for 2015, 2016, 2017  
462 and 2018. The produced map shows that some sub-basins are always characterized by a high  
463 amount of runoff. The runoff susceptibility map, realized considering the four yearly maps indicates  
464 the same sub-basins as high susceptible to runoff. Inside these areas, characterized by high  
465 urbanization, short runoff times could occur, increasing the peak flow downstream and  
466 consequently the flood risk. This elaboration represents a valuable tool for managing  
467 implementation plans and preventive targeted actions for those areas more susceptible to runoff  
468 generation. The general approach here employed can be adopted in many other small watersheds  
469 characterized by Mediterranean climate and highly anthropized.

470

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