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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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15	Abstract

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

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

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

several factors like: i) a good fit with real data, ii) the simulation/calibration time needed to obtain reasonable results and iii) the benefit in term of CPU time and field analysis. A total susceptibility map of runoff for the whole basin was also produced accounting for the results of the four simulated years, and it was compared with the observed flooding events. A further evaluation of runoff events for the near future (2040) was also applied, using a downscaled future climate projection of the global climate model (GCM) CNRM-CM6-1 (WorldClim, 2020), to highlight how the predicted 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 of Ancona city on the Adriatic coast (Figure 1). The Aspio watershed is characterized by the 99 100 presence of small hills with smoothed shape. The Aspio river springs are located at the confluence of the Offagna, Polverigi and Gallignano ditches, and gather the surface waters of Ancona, Conero 101 Mount and Osimo hills. The Aspio river, the main surface water course of the basin, is a tributary 102 103 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 and marly clays with sandstone layers, and iii) the Quaternary continental deposits made up of silty 105 clay, clayey sand and eluvial-colluvial deposits (Tazioli et al., 2015). Folds with gentle slopes and 106 faults with Apennines and anti-Apennines direction are present in the area. Most of the hills are 107 formed by the Mio-Plio-Pleistocene sequence that gives rise to a peculiar morphology made of 108 gentle ridges and large depressions. The Plio-Pleistocene basin developed along the main tectonic 109 110 faults and underwent a compressive phase, which was responsible for the final geomorphological evolution of the area (Mirabella et al., 2008). In the Aspio watershed the Quaternary eluvial-111 colluvial covers are made of sands, silty-sands and clayey silts and can reach a thickness of up to 112 113 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, with an average precipitation of about 800 mm/y in the valleys and 1200 mm/y in mountainous 115 116 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, commercial and industrial units, that are mainly located in the center of the watershed. Agricultural 118

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



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

130

131 2.2 Soil and Water Assessment Tool (SWAT) Model

132The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998; Arnold et al., 2012) was

initially developed by the United States Department of Agriculture (USDA) to simulate the effects

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

151

152 **2.3 Model set-up**

153 The SWAT model for the Aspio basin has been built using information concerning morphology, land cover, soil properties and climate data. The ArcSWAT 2012 version on ArcGIS 10.2 platform 154 has been used for the elaboration in this work. In Table S2 all the sources of the utilized data are 155 listed. For the realization of a regular SWAT simulation three main steps are needed. First, using 156 157 the "Watershed automatic delimitation" all the topographical inputs were calculated starting from a 20 m resolution Digital Elevation Model (DEM) to define the watershed features like boundaries, 158 159 river network, sub-basins, and to derive slope-related parameters. For the Aspio basin, an area of 155 km² has been divided in 33 sub-basins (Figure 2) with a minimum and maximum elevation of 160 8 m and 540 m above sea level (a.s.l.), respectively. The second phase includes the HRU definition, 161 intersecting data of slope, land cover and soil property information. The slope ranges were 162 163 established using the 20 m resolution DEM and classified in 3 classes: less than 5°, between 5° and

15°, and more than 15°. As no significative changes in land use were recorded in the last 20 years, 164 the CLC map for 2018 has been used for HRU delimitation. Eleven land covers were identified 165 (mainly industrial, residential, agricultural and agro-forestry) and homogenized with SWAT2012 166 crop's default database. Regarding soils' properties, SWAT requires the information about soil 167 hydraulic conductivity (Ks), soil water content, texture, percentage of organic carbon, soil albedo 168 ad more. For this study three different soil maps have been used (Figure S1), inasmuch, the soil 169 170 properties represent one of the three information needed in the construction of the HRU. The first simulation (SL1) utilized the soil information derived from the Digital Soil World Map (DSMW; 171 FAO, 2007) with a scale of 1:5 million. According to FAO DSMW classification (Figure S1a), the 172 Aspio basin is characterized by one soil category (Eutric Gleysol) with a Ks of 7.32 mm/h, a soil 173 bulk density (BD) of 1.3 g/cm³ and an available water capacity (AWC) of 0.164 mm H₂O/mm of 174 175 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 done using at least 3 Ks values of the topsoils (Figure S1b) measured with a double ring 177 178 infiltrometer in the respective geological formations, while all the other parameters have been integrated using the SWAT soil's default database selecting the soil type and texture. Thirteen soil 179 180 formations (Figure S1c) were identified with a Ks ranging from 0.35 to 324 mm/h, an average BD of 1.5 g/cm³ and AWC values from 0.073 to 0.175. The last simulation (SL3) was constructed using 181 182 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 basin. Soil data for SL2 and SL3 come from previous analyses realized by Università Politecnica 184 185 delle Marche (Mattioli, 2012) and are shown in Table S3 together with soil data for SL1. Parameters like Ks, clay, silt and sand content have been measured in the field while the values of AWC and 186 BD were adjusted using a hydraulic property calculator and integrated with the default SWAT2012 187 input database's values. For all the three simulation 33 sub-basins were created and further divided 188 into HRU, using a threshold of less than 10% for land use, for soil type, and slope. The HRU 189 threshold was employed to further discretize each sub-basin, especially for SL2 and SL3 where a 190 191 great heterogeneity in land use, soil and slope was found (Her et al., 2015). The last necessary input are the meteorological data. SWAT asks for daily variables of precipitation, temperature, relative 192 humidity, solar energy, and wind speed. Among these parameters, precipitation is directly involved 193 in the runoff calculation, and together with temperatures, wind speed, humidity and solar radiation, 194

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

217



Figure 2: SWAT model setup for the Aspio basin containing watershed subdivision, slope classesand land use dominance.

222 2.4 Calibration and validation

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

$$238 \qquad R^{2} = \left(\frac{\sum_{i=1}^{n} (K_{predicted} - \overline{K}_{predicted})(K_{measured} - \overline{K}_{measured})}{\sqrt{\sum_{i=1}^{n} (K_{predicted} - \overline{K}_{predeicted}) * \sum_{i=1}^{n} (K_{measured} - \overline{K}_{measured})}}\right)^{2}$$
(1)

239
$$NSE = 1 - \frac{\sum_{i=1}^{n} (K_{predicted} - K_{measured})^2}{\sum_{i=1}^{n} (K_{predicted} - \overline{K}_{predicted})^2}$$
(2)

240
$$PBIAS = \left(\frac{\sum_{i=1}^{n} (K_{measured} - K_{predicted})}{\sum_{i=1}^{n} K_{predicted}}\right) * 100$$
(3)

241

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

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

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

251

252 **3 Results and Discussion**

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

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

275

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

Table 1: List of parameters used for model calibration.

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

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

293

Table 2: Sensitivity analysis results and calibrated values for SL1, SL2, and SL3. For parameters
 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	0.00	0.00	0.00	-0.35	-0.41	-0.35
CH_K2.rte	0.00	0.00	0.00	21.2	26.50	27.50
ALPHA_BF.gw	0.00	0.28	0.00	0.00	0.05	0.00
SOL_AWC.sol	0.00	0.65	0.00	0.14	0.00	0.25
ESCO.hru	0.01	0.68	0.00	0.82	0.84	0.84
SOL_BD.sol	0.02	0.16	0.03	-0.41	-0.25	-0.36
GW_REVAP.gw	0.28	0.24	0.80	0.14	0.15	0.14
ALPHA_BNK.rte	0.43	0.92	0.30	0.06	0.00	0.05
SOL_K.sol	0.65	0.01	0.04	-0.28	-0.28	-0.45
GW_DELAY.gw	0.88	0.28	0.90	222	200.0	255.0
CH_N2.rte	0.98	0.17	0.93	0.15	0.13	0.17

296

Among the eleven chosen parameters, eight sensitive ones have been detected to be important in 297 298 regulating the streamflow generation for all the simulations (bold values in Table 2). Each simulation differs for the type of sensitive parameter and for its relative weight: i) for SL1, SCS 299 300 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 evaporation factor and baseflow factor (ALPHA_BF) were identified as the factors that produced 302 the higher impact on streamflow simulation, ii) in SL2, besides CH N2, CH K2 and ALPHA BF 303 304 also soil hydraulic conductivity (SOL_K), groundwater delay time (GW_DELAY), and Manning's value (CH_N2) were detected as sensitive parameters, and iii) for SL3 the result is almost the same as for SL1, with the only introduction of SOL_K. These results indicate that the greater number of soil units are considered, the more importance is gained by the hydraulic conductivity (SOL_K) in the streamflow/runoff generation. So, after the first interaction, the following ones were started using only the eight sensitive factors for SL1, SL2 and SL3 to obtain the fitted parameters' values (Table 2). The final calibration performances of the three models (SL1, SL2 and SL3) were assessed using three statistical indices and are reported in Table 3.

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Table 3: Performance analysis of the SWAT model in simulating streamflow during the calibration
 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)	≥0.50	0.76	0.65	0.71
Nash-Sutcliffe efficiency (NSE)	≥0.50	0.65	0.36	0.42
Percent bias in volume (PBIAS)	±25	6.1	-56.1	-32.9
CPU time for 100 runs (minute)		60 min	150 min	115 min

315

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

streamflow overestimation shown in Figure 3. Moreover, ordering the simulations according to the 331 number of soil units employed, a general linear decrease of the statistical indices from SL1 (one 332 soil) to SL3 (three soils) and finally to SL2 (thirteen soils) is recorded. This finding agrees with 333 Chaplot (2005), which stated that not always the extra cost and labor to obtain the greatest precision 334 in input, like soil characteristics, bring to more accurate predictions. So, considering that SL2 and 335 SL3 despite involving more detailed information have showed the worse simulation results, SL1 336 has been chosen as reference simulation for the validation procedure. It is also true that SL2 and 337 SL3 showed a good R^2 with real data, following the same trend, but with higher predicted volume. 338 It is surely possible that with further modifications of some soil parameters, together with more 339 calibration runs, those simulations could bring to better results but, at the same time, this could be 340 341 highly time consuming and not cost effective. So, there are several main reasons why the SL1 has been chosen: i) open access database has been used (no field analysis needed), ii) less space 342 requirement and iii) an acceptable simulation time to achieve satisfactory results. The model's 343 performance for the calibration and validation periods are represented in Figure 4. Both calibration 344 and validation are satisfactory with NSE and $R^2 \ge 0.50$ and PBIAS \pm 25%. For the validation 345 procedure all the three statistical indices are in the range of a "good" calibration with a R² of 0.80. 346 an NSE of 0.60 and a PBIAS of -15.35%. The streamflow representation in Figure 4 confirms a 347 little underestimation for the calibration (positive PBIAS) and an overestimation for the validation 348 349 procedure (negative PBIAS), but in any case within the acceptable range (PBIAS $\pm 25\%$). In general, SL1 shows a satisfactory model performance especially in simulating the highest peaks of 350 streamflow. 351



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



356 Figure 4: SWAT calibration/validation for SL1.

357

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

Following the calibration/validation procedure, the SWAT model was run for the period 2015-2018 in the entire basin. Among the available model's outputs, it was chosen to integrate the SWAT output SURQ (Surface runoff contribution to streamflow during time step, mm H₂O) for the 4 years

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



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



Figure 6: Total runoff susceptibility map for the Aspio basin.

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

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



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

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

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

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

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