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## **Assessing soil water content variation in a small mountainous catchment over different time scales and land covers using geographical variables**

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## 1 Introduction

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Soil water content (SWC) is a key variable in hydrology because it affects soil-atmosphere interactions that control hydrological processes at the catchment scale (Quinn *et al.*, 1993; Bogena *et al.*, 2010). SWC observations are used for data aggregation, hydrological modeling, and upscaling (Romano, 2014) to study processes such as drought (Broedel *et al.*, 2017; Abdelli *et al.*, 2017), flood forecasting (Hapuarachchi *et al.*, 2011), soil-surface exchanges (Tromp-van Meerveld and McDonnell, 2006), rainfall-runoff transformations (Tramblay *et al.*, 2010), and aquifer recharge (Dobriyal *et al.*, 2012). Studying SWC spatio-temporal variability is a challenge because it is determined by numerous factors such as atmospheric forcing, topography, soil properties, and vegetation, which interact differently according to seasons and moisture conditions (Grayson and Western, 1998; Western *et al.*, 2004). Most studies on SWC spatial organization have focused on SWC temporal persistence through the identification of stable patterns (Comegna and Basile, 1994; Mohanty and Skaggs, 2001; De Lannoy *et al.*, 2006; Hu *et al.*, 2010). But in the case of flood generation processes, especially flash flood, the mapping of SWC is required at very short time steps (less than 20 min) to get the event dynamics. For example, event-scale SWC variation maps are needed for the identification of runoff-contributing areas dynamics within catchments. High frequency SWC mapping remains a methodological challenge because areal SWC estimation depends on both the investigation scale and the measurement technique (Robinson *et al.*, 2008) but also on the high heterogeneity of soil in three dimensions.

Several methods have been recently developed to measure SWC at the catchment scale. For example, airborne monitoring has emerged in recent years. These methods are based on remote sensing approaches using passive and active micro-waves as well as radar or multi-spectra waves (Ochsner *et al.*, 2013) that are characterized by a limited spatio-temporal resolution and accuracy (Brocca *et al.*, 2012) even if new generation of SWC estimated from Sentinel-1 are produced at

27 high resolution in agricultural areas (El Hajj et al., 2017). Indeed, remote sensing provides  
28 observations at a resolution coarser than what is required for hillslope monitoring. Moreover,  
29 satellite soil moisture is generally representative of surface soil moisture because sensors cannot  
30 explore deep through the soil. The development of airborne based sensors (thermal infra-red)  
31 makes it possible to monitor soil moisture with higher accuracy and geometric correction has  
32 become easier with recent photogrammetry and drone mapping software but sensors and flight  
33 missions are expensive and time consuming especially in mountainous environments (Baghdadi,  
34 2005). Space-averaged SWC is also assessed from the non-invasive cosmic ray sensor, which  
35 provides time-lapse measurements in a limited area defined by a radius of 300 m around the  
36 sensor (Zreda et al., 2008; Bogena et al., 2013; Köhli et al., 2015). But SWC estimation is  
37 integrated over a 30 ha area and SWC variation over the measurement area is unknown.  
38 Hydrogeophysical techniques such as Ground Penetrating Radar (Huisman et al., 2003; Dubreuil-  
39 Boisclair et al., 2011), Electrical Resistivity Tomography (Zhou et al., 2001), multi-temporal  
40 resistivity measurements (Brunet et al., 2010) and Electromagnetic Induction (Kashanoski, 1988)  
41 have also been used to estimate SWC spatial variability (Michot et al., 2003) on transects,  
42 hillslopes, and fields. The pedotransfer function approach has been tested using the relationship  
43 between soil electrical resistivity and soil moisture (Brillante et al., 2014). But SWC retrieval from  
44 these techniques is discussed, especially due to their site-dependence (Calamita et al., 2015). At  
45 the hillslope scale, recent studies showed that the use of fiber-optic distributed temperature  
46 sensing (Selker et al., 2006; Cao et al. 2016) could be a valuable approach for 2D observation of  
47 soil water dynamics but this innovative method needs a complex calibration procedure according  
48 to soil type (porosity, mineralogy, diffusion coefficient) (Krzeminska et al. 2012).

49  
50 In most cases, SWC rate variations across scales have been estimated from a network of  
51 local ground-based sensors. In situ SWC plot scale measurements have been greatly improved in  
52 the last several decades due to new technologies and devices allowing monitoring in almost all

53 kind of soils. Invasive methods such as Time Domain Reflectometry (TDR) (Topp *et al.*, 1980),  
54 Frequency Domain Reflectometry (FDR) (Jones *et al.*, 2005; Vereecken *et al.*, 2014), and Time  
55 Domain Transmissometry (TDT) (Blonquist *et al.*, 2005) make it possible to produce SWC time  
56 series along vertical or horizontal profiles (Martini *et al.*, 2017) using soil dielectric permittivity  
57 measurements. Nowadays, these probes are usually available at affordable prices and are easy to  
58 install in the field. However, significant uncertainties regarding actual values may arise owing to  
59 the derivation of SWC from the permittivity measurement or the sensor raw signal *via* calibration  
60 equations that depend on temperature and soil texture. Several methods have been proposed to  
61 obtain soil moisture maps at higher spatial and temporal resolution from plot scale  
62 measurements, primarily based on geostatistical analysis (Western *et al.*, 1999; Brocca *et al.*,  
63 2010), temporal stability analysis (Vachaud *et al.*, 1985; Zhu *et al.*, 2020), the use of empirical  
64 orthogonal functions (Jawson and Niemann, 2007), or wavelet coherency analysis (Biswas and Si,  
65 2011). Most of these geostatistical approaches have referred to multiple correlation analysis and  
66 variogram models (Ver Hoef, 1993). Geostatistical analyses aim at establishing space-time  
67 relationships between SWC and local variables such as porosity or soil electrical conductivity  
68 (Kachanosky *et al.*, 1990; Brevik *et al.*, 2006 ; Altdorff *et al.*, 2017), topography as a control of  
69 vegetation, soil depth, and by extension, evaporation and evapotranspiration processes (Blyth *et*  
70 *al.*, 2004), or land use (Bardossy, 1998).

71

72         Several recent studies using those techniques have investigated the links between land  
73 surface characteristics and the spatial distribution of SWC at the catchment scale, as well as the  
74 link between topography and SWC/runoff thresholds (Vanderlinden *et al.*, 2012; Penna *et al.*,  
75 2013; Braud *et al.*, 2017). They have highlighted that these controls are very different according to  
76 the catchment geographic, climatic and physiographic properties. In a 1.9 km<sup>2</sup> alpine headwater  
77 catchment in the Italian Dolomites, Penna *et al.* (2011) observed that riparian zones reached  
78 rapidly saturation and contribute mainly to low runoff ratios. Conversely, high runoff ratios were

79 associated to subsurface flows on hillslopes occurring during wet period when soils were close to  
80 saturation and flowpaths between the hillslope and riparian zone became connected (Sidle *et al.*,  
81 2000; Ocampo *et al.*, 2006; Zuecco *et al.*, 2013; Mallet *et al.*, 2018). This study also showed that  
82 during dry period streamflows occurred before SWC reached saturation and conversely during  
83 wet period. In a 0.08 km<sup>2</sup> forested catchment in Pennsylvania (USA), Fan *et al.* (2020) observed  
84 that SWC temporal variability was higher on north facing hillslopes compared to south facing  
85 hillslopes and that downslope areas were usually wetter than upslope areas. They also observed  
86 that SWC became spatially more variable but temporally more stable with depth, which was also  
87 observed by Zhu *et al.* (2020) in a subalpine semi-arid catchment in China. The same observation  
88 was made between dry warm seasons and wet cold seasons. Slope shape also impact SWC spatial  
89 variability, storage and water availability for runoff (Moore *et al.*, 1988; Liu and Luo, 2010; Corrao  
90 *et al.*, 2017). Concaved slopes favor water concentrations which lead to higher SWC spatial  
91 variability compared to flat areas. Conversely, convex slopes have shallower infiltration depth and  
92 lower near surface SWC (Green and Erskine, 2011). Vegetation cover and land use also have a  
93 strong impact on SWC spatial and temporal variability since it's highly correlated to topography  
94 (Vereecken, 2008). SWC variability among different vegetation types depend on complex variables  
95 such as vegetation coverage, root distribution and depth or tree size and spacing  
96 (Rodriguez-Iturbe, I., 2000; Ni *et al.*, 2019; Wei *et al.*, 2019; Stevens *et al.*, 2020). Eventually,  
97 geostatistical analyses help fill spatial SWC data gaps at the catchment scale but producing high  
98 frequency SWC maps at the event time scale in a mountainous catchment remains a  
99 methodological challenge (Tromp van Meerveld *et al.*, 2009).

100  
101 SWC monitoring in sloppy catchments is challenging because they are highly complex.  
102 Topography and climatic forcing intensity and variability can make it difficult to access a large area  
103 of the catchment. Focusing on the hillslope scale is a way to monitor hydrological processes at  
104 smaller scale but some studies warn about the unique behavior of each hillslope which makes

105 their monitoring inappropriate to understand the catchment hydrological behavior (Beven, 2000;  
106 Sivapalan, 2003). These studies highlight the heterogeneity of soil hydraulic conductivity, lateral  
107 and vertical flow paths, soil depth and layers. To study subsurface flow processes in the Panola  
108 Mountains (PMRW, USA), Meerveld *et al.* (2006) developed a complex monitoring on a single  
109 hillslope. This kind of monitoring is very effective but difficult to reproduce elsewhere in the  
110 catchment because of its cost and extent. In arid badlands, Gallart *et al.* (2013) showed how  
111 complex it is to monitor soil water content because of the lack of vegetation and shallow soils.  
112 The lack of vegetation associated to sloppy areas induces large erosion rates and mass  
113 movements. Intense storms and wind erosion contributes to the development of dense gully  
114 network which make it difficult to make long time soil water content monitoring. In the Zin Valley  
115 badlands (Israel), Khun *et al.* (2004) studied runoff generation processes on hillslopes without soil  
116 water content probes because there is almost no soil layer. Moreover, only extreme rainfall  
117 intensities can generate runoff but at the same time high erosion rate.

118

119 In a mountainous, highly erosive environment, previous studies in the Draix-Bléone research  
120 observatory have focused on rainfall impacts on runoff and erosion rates (Borges, 1993; Descroix  
121 *et al.*, 2003), but also on infiltration processes in heterogeneous marl formations (Garel *et al.*,  
122 2012), and on the discrimination of contributing reservoirs to outflow during flood events (Cras,  
123 2007). Experiments have highlighted the strong variability of infiltration rates in black marl (from  
124  $9.E-7 \text{ m.s}^{-1}$  to  $1E-5 \text{ m.s}^{-1}$ ) and the difficulty of precisely following water fluxes due to the diversity  
125 and complexity of the marl structure (Mathys *et al.*, 2006). Moreover, making direct  
126 measurements or field observations is not possible during rainfall events due to flash flood  
127 hazards. During inter-flood periods, field instrumentation is often damaged due to changes of  
128 river morphology or hillslope instability. This situation is common in headwater catchments and  
129 explains why soil water content has only been little investigated in such environments. The  
130 present study is innovative as it is the first attempt to measure in such environments water

131 content continuously at the catchment scale and not just on a plot, a hillslope, or a vertical  
132 profile. Moreover, measurements are made in different land covers and not only in bare areas.

133

134 In this context, the main objective of this study was to explore the short time SWC dynamics  
135 in a mountainous highly reactive headwater catchment and its distribution over area from a set of  
136 plot scale sensors. A capacitance sensors network has been used to monitor SWC every 15 min at  
137 the catchment scale in forest, grassland, and black marl (bare soil) during the summer and  
138 autumn periods. The resulting data were used as input in a geostatistical model that links SWC to  
139 catchment geomorphological variables by regression and kriging. The specific objectives of the  
140 study were to: 1/ analyze how geographical variables influence SWC variations at different time  
141 steps, 2/ quantify the relationships between rainfall, SWC, vegetation cover and outflow at the  
142 event scale, 3/ examine event scale SWC dynamics among land covers to identify partition  
143 between subsurface flow types.

144

145

## 146 **2 Survey area**

---

147

148 The study area is the Laval catchment, located within the Experimental Research Hydrological  
149 Network Draix-Bléone in the Southern Alps, France (part of the eLTER infrastructure DEIMS.iD:  
150 <https://deims.org/be7fcb7d-d3c2-486d-a437-4754d18ca1ca>). Instruments installed in the  
151 catchment have monitored outflow, rainfall and erosion (Fig. 1) since 1983. Outflows are  
152 measured at the outlet using a Parshall type gauging station. A rain gauge is installed at the outlet  
153 of the catchment while a second one is located on the ridges upstream. A weather station at the  
154 outlet of the catchment has provided data on wind speed and direction, solar radiation, relative  
155 humidity and air temperature since 2000. Analysis of aerial photographs made it possible to  
156 follow bare surfaces evolution since 1948. A first land use map was drawn up by Vallauri in 1997.

157 Recently, a LidAr survey provided a high spatial resolution DEM (1 m) (Sintegra, 2011). Elevations  
158 in this small torrential headwater catchment (0.86 km<sup>2</sup>) range from 850 m at the outlet to 1200  
159 m. The Laval catchment is known for its high specific discharges during flood events, which may  
160 exceed 10 m<sup>3</sup>/s/km<sup>2</sup> (Mathys *et al.*, 2003). The local climate is sub Mediterranean with continental  
161 trend (Joly, 2010) and is defined by high solar radiation (> 2300 hour / year) with mild winters  
162 (little snow cover) and very dry summers. Mean annual rainfall is 800 mm (STD = 170 mm;  
163 observed period from 1987 to 2015). The local relief and the presence of material that is  
164 extremely sensitive to erosion (black marl of Bathonian, Callovian, and lower Oxfordian ages)  
165 explain the permanent dense gully network. Rainfall impact varies across seasons with high  
166 rainfall intensity during summer storms whereas spring and fall events are characterized by lower  
167 intensity and longer duration rainfall. Previous studies have provided detailed information on soil  
168 types (Maquaire *et al.*, 2002), soil properties (hydraulic conductivity, porosity, bulk density)  
169 (Malet *et al.*, 2005), and black marl sensitivity to runoff (Mathys *et al.*, 2005).

170

171

172

173

174 **Fig. 1. Survey area - Laval headwater catchment - ORE Draix-Bléone - Alpes-de-haute-Provence - Southern French**  
175 **Alps**

176

177

### 178 **3 Material and method**

---

179

180 The methodological approach developed in this paper to better understand SWC variation in  
181 space and time consists in 3 steps (Fig. 2): 1/ Designing a capacitance sensor network to monitor  
182 SWC between 10 and 20 cm depth in various land use and soil types. Once the probes are setup in

183 the field, they are calibrated using soils samples extracted at each probe location. 2/ Monitoring  
184 SWC at a 15 min time step in addition to rainfall and outflow measurements to study the  
185 catchment hydrological behavior at the event time scale. 3/ Estimating SWC using a geostatistical  
186 model based on geographical variables to represent the probe location situation. 4/ identifying  
187 the dominant flow mechanism on hillslopes at the event time scale from the wetting curve  
188 maximum slope method (Lozano-Parra et al., 2015).

189

190 **Fig. 2. Overview of the methodological approach**

191

### 192 **3.1 In situ measurements**

193

#### 194 **3.1.1 *Presentation of capacitance sensors***

195

196 Selected sub-catchments were equipped for SWC monitoring from May 2016 to November  
197 2016. This investigation was based on FDR probes (10HS by *Decagon Devices*®). Less expensive  
198 than TDR and relatively easy to set in the soil, the 10HS probe makes it possible to measure SWC  
199 continuously on large scale through a network of autonomous sensors. The soil and the probe  
200 electrodes are used as a capacitor whose capacity varies according to the soil dielectric  
201 permittivity which is related to the presence of water (Qu et al., 2013). The sensor uses a 70 MHz  
202 frequency that minimizes salinity and textural effects, and the 10 cm long probe has an influence  
203 volume of about 1.3 liter. Fourteen capacitance probes were set up in different soil types in the  
204 survey area: 4 in the black marl, 4 in grassland, and 6 in forest (Table 1). The monitoring was  
205 carried out using a 15 min time step. The 10HS probes were vertically positioned to give an  
206 average SWC between -10 cm (bottom of electrode) and -20 cm (top of electrode) depth. At the  
207 plot scale, SWC was also measured vertically using PR2 probes (*Delta-T Devices*®). These sensors  
208 were carried on to different points and measurements were done into a plastic tube. SWC were

209 obtained at four depths (10 cm, 20 cm, 30 cm and 40 cm) by measuring the dielectric constant of  
 210 the soil using capacitance/time domain technology. Vertical monitoring from May to June 2016  
 211 showed that most SWC variations occurred between 10 cm and 20 cm in grassland and forest in  
 212 the study area. It is important to note that some astonishing behavior could be monitored due to  
 213 improper set up. Indeed, FDR probes present a high sensitivity to soil contact and can be strongly  
 214 impacted in case of air gaps between the soil matrix and the sensor. Air gaps are due to black marl  
 215 structure complexity and instability near surface, to stones and tunnels created by animals  
 216 especially in grassland, and mainly to roots and stones in forest, but also to freeze/thaw process  
 217 (Mallet, 2018).

218

219 **Table 1. Soil type and properties at the plot scale**

220

221 222	Plot	Land Cover	Classification (INTL)	Porosity	Bulk density (kg/m <sup>3</sup> )	Slope	Orientation
223	B1	Black marl	Clay loam	0.302	1.86	30	SE
224	B2	Black marl	Clay loam	0.356	1.73	10	S
225	B3	Black marl	Clay loam	0.409	1.55	25	NE
226	B4	Black marl	Clay loam	0.414	1.54	30	NE
227	F1	Forest	Silty loam	0.469	1.40	5	S
228	F2	Forest	Silty loam	0.434	1.49	15	W
229	F3	Forest	Silty loam	0.452	1.45	15	N
230	F4	Forest	Silty loam	0.502	1.32	15	N
231	F5	Forest	Silty loam	0.447	1.46	15	N
232	F6	Forest	Silty loam	0.494	1.36	20	NW
233	G1	Grassland	Silty clay loam	0.498	1.33	15	S
234	G2	Grassland	Silty clay loam	0.457	1.40	20	SW
235	G3	Grassland	Silty clay loam	0.466	1.41	20	SW
236	G4	Grassland	Silty clay loam	0.457	1.41	10	SE

237

### 238 **3.1.2 Calibration of 10HS capacitance sensors**

239

240 SWC values were obtained from soil electrical permittivity, which was computed from the  
241 raw 10HS probe signal. SWC data obtained from 10HS probe using the third-order polynomial  
242 calibration function provided by the manufacturer (Decagon Devices, 2016) were compared to  
243 water content values extracted from in situ soil samples collected from depths of -10 cm to -20  
244 cm. Soil samples were collected from each plot scale using 10 cm long cores (from -10 cm to -20  
245 cm depth) under different hydric conditions. Results showed that SWC monitored in forest fitted  
246 the manufacturer theoretical law. A different calibration function was developed from soils  
247 sampled in grassland and black marl (Mallet *et al.*, 2018). Sensor accuracy was found to be +/- 3%  
248 in forest and +/- 4% in grassland and black marl, which is a reasonable estimate of mean SWC  
249 patterns at the watershed scale.

250

### 251 **3.1.3 Network optimization**

252

253 Studying spatial variability of water content in the upper soil layer is a complex task as it strongly  
254 depends on the scale of analysis. Using a sensor network continuously measuring SWC makes it  
255 possible to get spatial data at small scales such as plots, transects, hillslopes and small  
256 catchments. Regarding the Laval catchment size, the survey budget, manpower, and the distance  
257 from the lab to the experimental field, a network of few sensors was setup to provide data at the  
258 plot scale (Blume *et al.*, 2009). To optimize the spatial distribution of the network, homogeneous  
259 soil-landscape patterns with potentially specific hydrologic behaviors were delineated (Dehotin  
260 and Braud, 2008). Such landform-units were defined according to hydrological criteria (stream  
261 network and sub-catchment classification), land cover, soil type, and topography (slope, hillslope  
262 orientation). In this study, a four-step method has been applied (Fig. 3) as follows:

263

264           **1/** Sub-catchments were delineated using the Strahler stream network classification  
265 (Strahler, 1952; Le Barbu, 2006). Only sub-catchments of order 3, 4 and 5 whose main talweg is  
266 connected to the main network were selected for this stage. They represent a minimum surface  
267 of 1 ha which exceeds the surface of an elementary gully whose hydrological behavior is already  
268 known (Mathys, 2006).

269

270           **2/** Theoretical surface flow concentration areas were then mapped using the RuiCells cellular  
271 automaton (Langlois and Delahaye, 2002) which establishes a link between topographic variables,  
272 the catchment morphology (size and form), and hydraulic variables. Using a 10 m DEM (1 m DEM  
273 could not be used because of the model computational capacities), a spatially homogeneous  
274 rainfall, and considering a zero infiltration capacity of the soil, Ruicells produces a surface flow  
275 concentration map. Surface flow concentration is computed at each sub-catchment outlet by the  
276 Concentration Index (CI) which takes into account the density of the stream network upstream of  
277 each sub-catchment outlet (Douvinet *et.al*, 2015). The produced map makes it possible to better  
278 understand the catchment potential hydrological response from the sub-catchment to the final  
279 outlet (Douvinet, 2008). For instance, very marked surface water flow concentrations (CI > 10) can  
280 be observed at the outlets of several sub-basins of orders 3, 4 and 5 and at several confluences (in  
281 the main network) while some sub-catchments show very low IC index. This step highlights the  
282 heterogeneity of the catchment potential hydrological response and helps to identify potential  
283 SWC measurements plots.

284

285           **3/** The percentage of bare and vegetated surfaces (forest, grassland) was then calculated on  
286 the sub-catchments and compared with the potential surface flow concentration areas identified  
287 in step 2. Sub-catchments marked with CI > 10 have various land covers: the proportion of  
288 vegetated areas varies from 11% to 82%, while bare soils are between 17% and 88%. It is

289 therefore interesting to target the investigation on sub-catchments with various CI and land  
290 cover. Eventually, four sub-catchments with various size, morphology, land cover, soil types and  
291 network ordination were selected for the investigation.

292

293 4/ Soil type map (Maquaire et.al, 2002) was then combined with land cover map which  
294 made it possible to identify the most represented land covers within the Laval basin. In order to  
295 concentrate the analysis on the most represented soil-vegetation units, only the first six classes  
296 obtained were retained which represent 72.9% of the Laval total surface.

297

298 5/ SWC probes were then setup in the six classes identified in step 4 within the selected sub-  
299 catchments in step 3. Final probe location depended on slope, hillslope orientation, and  
300 accessibility.

301

302 **Fig. 3. A four-step method to obtain an optimal capacitance sensors network in the study area**

303

304 Comparison of SWC values requires homogenous spatial distribution of rainfall over the  
305 catchment at the event scale. For this purpose, rainfall spatial variability was studied at the event  
306 scale with the addition of 3 rain gauges (*Rainwise*<sup>®</sup>) set up inside the catchment away from  
307 vegetation cover (Fig. 2). Their location was based on elevation, distance to the outlet, and  
308 accessibility (Table 2). Fourteen rainfall events were studied in 2016. For each event, each rain  
309 gauge data were compared to data measured at the catchment outlet (*Précis Mécanique*<sup>®</sup>).

310

311 **Table 2. Laval rain gauges**

312

313	Rain Gauge	Setup	Elevation (m)	Distance from outlet (m)
314	P0	1984	851	0

315	P1	2015	900	690
316	P4	2015	890	380
317	P6	2015	915	878

318

319

## 320 **3.2 Geostatistical modeling framework**

321

### 322 **3.2.1 *Presentation of LISDQS***

323

324 The LISDQS (Interpolation of Quantitative and Spatial Data) geostatistical model (developed  
 325 by Joly and Vuidel in 2008 and presented in Joly *et al.*, 2008) was used to estimate SWC at the plot  
 326 scale considering local geographical variables (Arnaud and Emery, 2000). LISDQS runs a global  
 327 analysis that computes all measurement plots to produce a single geostatistical model fitting for  
 328 all plots at each time step. Spatial interpolation of soil moisture measurements is performed by  
 329 the combination of linear regressions (LR) (Joly *et al.*, 2011) followed by kriging of the residuals  
 330 using the method « regression-kriging » (RK) described by Hengl *et al.* (2007). LR is used to fit the  
 331 explained variation with spatial predictors. The subsequent kriging process used to fit the  
 332 residuals, i.e. unexplained variation, is ordinary kriging fitted by a single variogram (Spherical  
 333 model) (Matheron, 1970; Gratton, 2002).

334

### 335 **3.2.2 *A three-step analysis method***

336

337 The LISDQS model combines kriging and regression in 3 steps: 1/ Linear Regression between  
 338 all SWC plot and local variables (topography, vegetation, soil) reveals the variables that best  
 339 explain the SWC space-time variations (highest  $R^2$  for  $P_{value} < 0.05$ ). These best explanatory  
 340 variables are then associated 2 by 2, 3 by 3, 4 by 4, etc... (from the best to the worst) in stepwise

341 multiple regressions (Hocking, 1976). The best combination (with the highest  $R^2$ ) is applied to all  
342 plots to obtain estimated values that are compared to measured values. 2/ Kriging shows the  
343 spatial structure of SWC distribution of residuals obtained in the first step. Kriging uses the semi-  
344 variogram properties and also computes residuals. 3/ Third step is Residual Kriging. At the end of  
345 the first step (LR) and the third step (RK), the estimated soil moisture values are validated by a  
346 "leave-one-out" cross-validation (Plutowsky *et al.*, 1994), the process of which is as follows: as  
347 many iterations are repeated as there are observations  $i$ . At each iteration, observation  $i$  is  
348 removed from the sample and the model runs with the new sample. Then using this new model,  
349 the predicted value of the withdrawn observation  $i$  is calculated. A series of predicted values is  
350 then obtained which can be compared with the observed values by calculating the residuals of the  
351 model. The residuals obtained at the end of phase 1 are estimated by kriging, those obtained at  
352 the end of phase 3 are used to estimate root-mean-square error (RMSE). This three-step method  
353 makes it possible to improve the spatial interpolation of SWC data by taking into account  
354 environmental heterogeneity.

355

### 356 **3.2.3 Parameterization**

357

358 The LISDQS geostatistical model automatically performs a sensitivity analysis for each time  
359 step. Linear regressions were computed between SWC measured at the plot scale and the mean  
360 value of local variables on a 9 m<sup>2</sup> area around the plot. This averaging method accounts for the  
361 environmental heterogeneity around the SWC probe and not only the value of a 1 m<sup>2</sup> plot. The  
362 linear regressions make it possible to identify the best variables among as many variables as  
363 needed to be tested.

364

365 SWC was driven by a set of local variables that are used in the geostatistical model. These  
366 variables drive different processes that affect SWC variations according to seasons and soil

367 moisture status. A high-resolution Digital Elevation Model (DEM) (LiDAR, 1m, Panissod *et al.*,  
368 2010) was used to derive 4 topographic variables: curvature index (slope convexity or concavity),  
369 soil depth, hillslope orientation defined by sinus (West-Est orientation) and cosinus (North-South  
370 orientation). The Normalized Vegetation Index (NDVI) was computed from a SPOT 6/7 image<sup>1</sup> to  
371 take into account the land cover influence. It is the most common vegetation index for identifying  
372 areas with an elevated chlorophyll activity which are related to vegetation. It computes the  
373 difference between red and near-infrared wavelengths and is normalized by the addition of both  
374 which reduces the ground lightness. NDVI was calculated from the only SPOT image that covered  
375 the survey area during the study period.

376

377 Cross correlation analysis showed that the NDVI was positively correlated to solar theoretical  
378 radiation which gives for each DEM pixel the solar radiation in W/m<sup>2</sup> at different time scales. The  
379 latter was weakly positively correlated to hillslope orientation ( $R = 0.55$ ), whereas slope was  
380 negatively correlated to NDVI ( $R = - 0.415$ ) (Table 3). In the study area, gentle slopes are mostly  
381 associated with vegetation, which are also among the sunniest areas, while steep slopes are  
382 mostly associated with gullies and bare areas. Soil depth was positively correlated to NDVI ( $R =$   
383  $0.58$ ) because soils develop with vegetation growth, whereas bare areas are prone to erosion.  
384 NDVI is related to interception and evapotranspiration, slope affects subsurface flows (horizontal  
385 or vertical), and solar radiation is associated to evapotranspiration whereas soil water storage  
386 mostly depends on soil depth. The solar radiation curve followed the same dynamic as NDVI and  
387 had an increasing positive correlation with SWC from July to mid-October. Soil depth had a stable  
388 positive correlation with SWC over the study period.

389

390 **Table 3. Correlation (R) between explanatory variables used for the geostatistical modeling.**

---

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	Sinus	Cosinus	NDVI	Curvature	Soil depth
Sinus	1	0.081	-0.538	-0.034	0.308
Cosinus		1	0.109	-0.04	0.631
NDVI			1	-0.286	0.598
Curvature				1	0.293
Soil depth					1

### 3.3 Identifying the dominant flow mechanism

Previous studies showed that surface runoff was the main hydrological processes during flood event in the Laval catchment. However, subsurface flow processes also play a key role on the catchment hydrological behavior. During rainfall, preferential flows contribute to fast wetting of shallow soil horizons and to outflows by rapid exchange from soil to streams. On the other hand matrix flows can be observed anytime and in every monitored land covers and affect soil moisture status and water availability for plants. During a rainfall event those two processes can occur simultaneously. To identify the dominant process, the method of the wetting curve maximum slope ( $S_{max}$ ) as proposed by Lozano-Parra *et al.* (2015) was used. This analysis aims at identifying which process is dominant, but not to quantify its contribution to discharge.

$$S_{max} = \max\left(\frac{\theta_{t+\Delta t} - \theta_t}{\Delta t}\right) * 10^4$$

This parameter represents the maximum soil water content increase measured at the event time scale by each probe between two measurements.  $\theta_t$  is the SWC value at the time  $t$ , and  $\Delta t$  is the 15 min interval between two measurements.  $S_{max}$  was used as an indicator for the degree of slow or fast flows. On this base, it was assumed that low  $S_{max}$  value was representative of matrix

417 flow while high  $S_{max}$  was associated to preferential flow (Fig. 4). Intermediate slopes were  
418 associated to a mix of both processes.

419

420 **Fig. 4. Examples of different soil moisture increases monitored during three different flood events.**

421

## 422 **4 Results**

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423

424 The results are divided in four sections that address the questions proposed in this paper.  
425 First, rainfall variability was studied to ensure that SWC data obtained at different locations could  
426 be compared and that the geostatistical analysis could be conducted. Then relationship between  
427 SWC and discharge was analysed to take into account the catchment near-surface hydric status  
428 impact on the catchment hydrological response. Measured and estimated SWC data obtained at  
429 daily, hourly and 15 min time scales were then compared to see how geographical variables could  
430 be used to determine SWC at the catchment scale under various land use and hydric conditions.  
431 Eventually, SWC variations at 15 min time step were analysed and compared to rainfall properties  
432 to enhance SWC space-time variation and impact on subsurface flow types.

433

### 434 **4.1 Low rainfall spatial variability at the event scale**

435

436 The event scale analysis showed low variability between the 3 rain gauges inside the  
437 catchment (differences ranged from 0.3% to 3.4%) (Fig. 5). On the other hand, differences (from  
438 0.4% to 21.5% of the cumulative rainfall event) occurred between P0 (located at the final outlet)  
439 and the other rain gauges, with higher cumulative values measured at P0 at the event scale (mean  
440 difference of 6.3%). The largest differences occurred during April 22 and June 16 events with  
441 cumulative rainfall lower than 31.2 mm (measured at P0). These differences come from the  
442 smaller diameter of P1, P4 and P6 compared to P0. The low spatial variations at the event time

443 scale showed that rainfall was relatively homogenous over the catchment, which made it possible  
444 to conduct the geostatistical analysis at the event scale.

445

446 **Fig. 5. Cumulated rainfall monitored by 4 rain gauges for 14 rainfall events in 2016. The number over the bar chart is**  
447 **the difference between the highest and the lowest rainfall values recorded by the rain gauges at the event time scale.**  
448 **No rainfall data available on February 7 and March 5 at P4 gauge.**

449

## 450 **4.2 Relationship between SWC and discharge**

451

452 Daily SWC variations provided an overview of the catchment wetting/drying dynamics  
453 over the study period (Fig. 6). Significant differences between measured SWC were observed  
454 among the three main land cover types.

455

456 SWC dynamics were similar in vegetated areas although a higher dispersion of SWC values  
457 was observed between forest plots (mean SWC difference of 3.9% between F1 and F4) as  
458 compared to grassland (mean SWC difference of 0.3% between G2 and G4) because forest  
459 sensors are setup on silty loams which have a higher water capacity than the other soils. F1 and  
460 F2 sensors globally monitored less variations than the other sensors located in forest. Soil  
461 evaporation which has been taken into account by the sensor placed at 10 cm has a strong  
462 dynamic especially during wetting period. While during dry period plants extract water in deeper  
463 layers and the sensor monitor less variations. It could also be explained by improper installation  
464 since F1 and F2 are installed in soils with a lot of roots and stones. The highest daily SWC was  
465 measured in forest (SWC = 41.8%) but the SWC variation (SWC max - SWC min) was lower than in  
466 the other land covers (SWC values ranging from 20.8% to 41.8% in forest, from 11.2% to 34.8% in  
467 grassland, and from 1.8% to 30% in black marl areas).

468

469 SWC dynamics was quite different among black marl plots (mean SWC difference of 8.7%  
470 between B1 and B2). SWC showed high amplitude (min = 2.5%; max = 30%) but daily SWC  
471 variations was smoother than what was observed in rooted soils. Only the B2 probe, located  
472 between bare soils and rooted soils, had a similar trend to that of vegetation probes with a short  
473 reaction to rainfall. The high variability of SWC across space and time in black marl showed that  
474 black marl had the capacity to store and release water during the entire study period which can  
475 be explained by the complexity of subsurface exchanges in this medium. This can be explained in  
476 particular by the spatial variability of infiltration between the different types of regoliths.  
477 Saturation hydraulic conductivities measured on hillslope summit were low which favored surface  
478 runoff. Saturation hydraulic conductivities measured on footslopes where weathered marl  
479 accumulated were higher and more propitious to infiltration (Mathys and Estèves, 2005).

480

481 During the study period, each rainfall events resulting in a flood event ( $Q_{max} > 500$  l/s)  
482 provoked variations on all SWC probes measurements (Fig. 6) as expected since rainfall was found  
483 to be quite homogeneous over the catchment. Conversely, some rainfall events did not led to  
484 outflow variations despite variations recorded on SWC probes. Between May and the end of  
485 November, only 7 rainfall events on a total of 16 with cumulative amount over 30 mm gave rise to  
486 floods with discharges over 500 l/s (except for the September 12 event with 18 mm rainfall  
487 amount). This rainfall threshold is consistent with past observations (Mathys, 2006).

488

489 **Fig. 6. SWC time-series data presentation. Daily mean SWC is monitored at 14 plots. River flows are measured at the**  
490 **Laval outlet by a Parshall flume. Rainfall was measured from May 11 until November 29 2016 at the Laval final outlet.**  
491 **Dashed lines indicate flood events (Discharge > 500 l/s).**

492

493 These catchment outflow variations partly depend on the relative soil dryness/wetness  
494 which controls the occurrence of overland flows on the hillslopes. Based on the total volume  
495 flowed over the event, this relationship is evidenced by the positive trend observed between the

496 initial water content and the runoff coefficient, except for the most exceptional flood events  
497 where direct surface runoff occur over the main part of the event (Fig. 7, red dot). Peak  
498 discharges are usually higher in autumn when the catchment is wet than in summer due to higher  
499 cumulative rainfall in autumn compare to summer rainfalls. However, no correlation was  
500 observed between the initial soil moisture and the maximum flow rate reached at the outlet. This  
501 result illustrates the variability of runoff conditions on the slopes at the peak discharge which  
502 change highly according to the events (dominant contribution of hortonian flow or subsurface  
503 flow).

504

505 **Fig. 7. Relationships between runoff coefficient and antecedent soil moisture at the event time scale. The runoff**  
506 **coefficient is the ratio (%) between the amount of water flow and the amount of water precipitated at the event**  
507 **time scale. Antecedent soil moisture is an average value computed from the values of each capacitance probe before**  
508 **rainfall.**

509

510

### 511 **4.3 Estimated SWC at daily and hourly time scales**

512

#### 513 **4.3.1 *Observed SWC VS estimated SWC***

514

515 To validate the geostatistical modeling, the model was run using SWC data from 11  
516 sensors instead of 14. Then the 3 remaining sensors (one in forest, one in grassland and one in  
517 black marl) were used to validate the model at the daily and hourly time scales which gave similar  
518 results (Fig 8). SWC were well estimated in all land uses throughout the study period. The mean  
519 error (+/- 2.3%) was lower than the in situ measurement error (from +/3% to +/- 4%). In spring,  
520 especially in May, SWC values were underestimated in all land uses. In summer, estimated SWC  
521 values fitted quite well with observations until August and early September rainfalls where  
522 estimated SWC values were overestimated in grassland and underestimated in forest and black

523 marl. Estimated SWC values appeared to be overestimated in grassland throughout fall especially  
524 from mid September until mid October. Conversely, estimated SWC values fitted with  
525 observations in forest and black marls despite underestimations in forest the days after long  
526 autumn rainfalls.

527

528 **Fig. 8. Model validation at daily and hourly time scales.**

529

530 Measured and estimated SWC values were compared using the linear least squares  
531 regression method. Variation of the determination coefficient ( $R^2$ ) gives an overview of the  
532 statistical analysis and how geomorphological variables can be used to estimate SWC variations  
533 over different time scales (Fig. 9). However,  $R^2$  values must be interpreted with care since there  
534 are only 14 data points in the regressions. First of all, correlations between measured and  
535 estimated SWC were better at the hourly time scale in May and June and from the October 14  
536 flood event until the end of November (catchment wetting period) while relationships were  
537 better at the daily time scale during summer (catchment drying period). SWC variations often  
538 appeared at the same time with higher amplitude at the hourly time scale and a smoother  
539 dynamics with the daily data. In most cases, higher correlations were observed during no rainy  
540 periods, namely during soil drying by drainage or evaporation losses. However, sharp decreases of  
541  $R^2$  were observed at both time scales during flood events. The loss of correlation with the  
542 catchment morphological features at that times shows that SWC variations were mostly  
543 controlled by rainfall intensity.

544

545

546 **Fig. 9. Relation between measured and estimated SWC ( $R^2$ ) at daily and hourly time scales.  $R^2$  were computed at both**  
547 **daily and hourly time scales by plotting the 14 measured SWC with the 14 estimated SWC to get one  $R^2$  value every**  
548 **time step. The relationships are significant over the “Student” red dot line.**

549

550 Time series plots show that SWC were generally correctly simulated in all land covers (Fig.  
551 10). Nevertheless, a few probes showed singular behaviors. For instance, B1 probe (black marl)  
552 was poorly simulated ( $R^2 < 0.4$ ) compared to B3 and B4 probes. Also, B1 probe measured very low  
553 SWC values from summer until the end of September while B3 and B4 were highly reactive to the  
554 first autumn rainfall event (September 12). It could be explained by improper setup and air gaps  
555 between the marl and the probe electrodes since B1 is installed between marls layers. This  
556 installation was hard but it was important to monitor that kind of zone since it is highly  
557 represented at the catchment scale. Measurements obtained at this location need to be  
558 interpreted with caution. In grassland, G1 probe showed a very low  $R^2 (< 0.2)$  with lower values  
559 and larger variation of the simulated SWC compared to observations. Conversely, F1 probe set up  
560 in forest measured higher SWC values and much lower variations than the estimated SWC. These  
561 shortcomings were assumed to be the result of improper set up.

562

563

564 **Fig. 10. Some examples of relationships between measured and estimated SWC ( $R^2$ ) at some plots in various**  
565 **monitored land covers at the hourly time scale.**

566

#### 567 **4.3.2 Weight of local geographical variables in the geostatistical model**

568

569 At both daily and hourly time scales, the weighted model gives information about  
570 wetting/drying processes using mainly 3 variables: soil depth, curvature index and NDVI. During  
571 wetting periods, the model estimated SWC by combining mainly curvature index and NDVI (Fig.  
572 11), except during high flows where rainfall intensity had a major impact on SWC variations.  
573 During drying periods, SWC was primarily estimated by combining soil depth and NDVI. NDVI  
574 weight never exceeds 20% but is constantly used over the study period as it is related to  
575 interception, evaporation and evapotranspiration processes. Curvature index controls drainage

576 processes and has a strong weight in the model during rainfall and from mid October until mid  
577 July. Soil depth has a strong weight from mid July until mid October as it is linked to recharge  
578 processes by controlling soil water storage capacity. In early fall (mid September until mi  
579 October), the weighted model varied using mainly soil depth, curvature index and cosinus (which  
580 is related to soil depth ( $R = 0.631$ )). No flood event appeared during this period but grouped  
581 rainfall events led to successive wetting/drainage processes at short time steps.

582

583

584 **Fig. 11. Representation of the primary weighting of local variables in the weighted model at both daily and hourly**  
585 **time scales.**

586

587

#### 588 **4.4 Estimated SWC at event time scale (15 min)**

589

##### 590 **4.4.1 *Observed SWC VS estimated SWC***

591

592 The overall relationship between measured and estimated SWC was computed from all 14  
593 capacitance probes for each of the 7 flood events that appeared from may until November 2016  
594 (Fig. 12). The relationship is statistically significant over a threshold of  $R^2 = 0.53$  ( $P_{\text{value}} = 0.05$ ). At a  
595 15 min time step, correlations between measured and estimated SWC ( $R^2$ ) had the tendency to  
596 decrease when rainfall intensity increased and in return to increase when rainfall stopped or  
597 intensity was very low ( $< 2$  mm/h at a 15 min time step). This increase of  $R^2$  during drainage is  
598 consistent with observations made at the daily and hourly time steps.  $R^2$  decreases were larger at  
599 the beginning of rainfall events. For instance, a rainfall intensity of 8 mm/h occurring at the  
600 beginning of the storm induced a higher  $R^2$  decrease than a rainfall intensity of 40 mm/h that  
601 happened almost 2 hours after the rainfall began (Fig. 12, October 14 event). The same

602 observations could be made during a long autumn rainfall (840 min) where a maximum rainfall  
603 intensity of 8 mm/h (at a 15 min time step) during the first part of the event caused a higher  $R^2$   
604 decrease (from 0.8 to 0.6) than a maximum rainfall intensity of 10 mm/h (at a 15 min time step)  
605 that occurred later (Fig. 12, November 21/22 event). Also, a delay was observed between rainfall  
606 and  $R^2$  variation induced by infiltration time and the different SWC rising times (for each probe,  
607 time between the beginning of rainfall and the change of the slope in the SWC rising). This delay  
608 was negatively related to rainfall intensity. SWC were better estimated during November storm  
609 flows caused by long rainfall events with low intensity when the catchment was wet (high mean  
610 SWC and low SWC variations). During summer, flood events caused by shorter and more intense  
611 rainfall when the catchment was dry (high SWC variations) resulted in poorer correlations.

612

613 **Fig. 12. Overall relationships between measured and estimated SWC ( $R^2$ ) at the event time scale.**

614

615 Time series plot shows that SWC dynamics were well estimated in most situations (Fig.  
616 13). Observed values were underestimated or overestimated according to the plot with a  
617 maximum deviation of about 5% water content. Nevertheless, singular behaviors were observed  
618 at few plots such as the absence of SWC reactions to rainfall (e.g. F1 and F2 probes) despite  
619 measurements recorded by the closest rain gauges under vegetation cover (10 m from F1 and 70  
620 m from F2). This could be explained by soil hydrophobia due to the absence of rainfall event since  
621 8 days. Moreover, no rainfall with amount over 6.8 mm happened since 16 days. Hydrophobia  
622 had already been observed in July 2015 during soil infiltration experiments.

623

624

625 **Fig. 13. Some examples of different kind of relationships between SWC measured and estimated during the June 16**  
626 **event.**

627

628 **4.4.2 Relationship between SWC and rainfall properties**

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At the event time scale, SWC variations mostly depend on rainfall intensity, which varies according to season, and on the initial SWC before rainfall which also varies according to land covers. The reaction time (*ReactT*) is defined as the time between the beginning of rainfall and the beginning of SWC increase at the sensor depth. Rising time (*RisT*) is defined as the time between the start of SWC increase at the sensor depth and the moment of the peak. Amplitude (*Amp*) is defined as the ratio between the SWC peak and the initial SWC value (before rainfall starts). *ReactT* (Table 4) was generally shorter in grassland than in black marl and forest. In black marl, the larger reactivity delay measured at the depth interval 10-20 cm can be explained by the material anisotropy due to marl layer bedding and orientation, which results in shallow preferential lateral subsurface flows (0 - 10cm) (Calvo-Cases *et al.*, 1991; Castillo *et al.*, 2003; Cantón *et al.*, 2011; Garel *et al.*, 2012). In forest areas, water reaches the soil with a delay that depends on tree canopy interception. *ReactT* observed during intense summer rainfall events was minimal in grassland. In black marl, the shortest *ReactT* was observed during autumn rainfall events. *Amp* dynamics in grassland and black marl were similar at the event time scale. Low *Amp* observed in forest areas was due to high SWC throughout the study period. Nonetheless, very similar SWC variations could be observed among all land covers during the November 24/25 rainfall event due to a high mean SWC value at the catchment scale (88.6 mm cumulative rainfall during the November 21/22 event). Eventually, there was a clear distinction between seasons, with shorter *ReactT* and *RisT* during summer events (June 16; June 18; September 12) than during autumn events (October 14; November 4/5; November 21/22; November 24/25).

**Table 4. Plot scale SWC variation at the event time scale - mean values by land cover.**

Event Rainfall	SWC rate variation	Black marl	Forest	Grassland
June 16				
Cumulative rainfall (mm)	31.2	Rising time (min)	65	61
				35

656	Mean intensity (mm/h)	5.43	Increase time (min)	190	240	170
657	Maximum intensity (mm/h)	24.0	Amplitude (%)	23.4	16.5	33.1
658	June 18					
659	Cumulative rainfall (mm)	36.8	Rising time (min)	50	40	35
660	Mean intensity (mm/h)	8.66	Increase time (min)	120	100	55
661	Maximum intensity (mm/h)	31.2	Amplitude (%)	17.1	12.2	17.8
662	September 12					
663	Cumulative rainfall (mm)	17.8	Rising time (min)	72	68	65
664	Mean intensity (mm/h)	4.45	Increase time (min)	172	130	70
665	Maximum intensity (mm/h)	28.8	Amplitude (%)	18.6	19.1	28.7
666	October 14					
667	Cumulative rainfall (mm)	54.2	Rising time (min)	122	138	55
668	Mean intensity (mm/h)	2.85	Increase time (min)	155	240	215
669	Maximum intensity (mm/h)	40	Amplitude (%)	35.4	23.1	28.7
670	November 4/5					
671	Cumulative rainfall (mm)	46.8	Rising time (min)	235	240	210
672	Mean intensity (mm/h)	1.66	Increase time (min)	1040	1075	1090
673	Maximum intensity (mm/h)	12	Amplitude (%)	25.6	19.2	17.2
674	November 21/22					
675	Cumulative rainfall (mm)	88.6	Rising time (min)	255	287	195
676	Mean intensity (mm/h)	2.38	Increase time (min)	965	1100	1430
677	Maximum intensity (mm/h)	9.6	Amplitude (%)	19.2	11.6	16.1
678	November 24/25					
679	Cumulative rainfall (mm)	98.2	Rising time (min)	30	63	50
680	Mean intensity (mm/h)	2.85	Increase time (min)	130	916	85
681	Maximum intensity (mm/h)	12.8	Amplitude (%)	15.2	15.7	18.5

682

683           Several parameters such as the cumulative rainfall, the number of days since antecedent  
684 rainfall events, rainfall duration, rainfall mean and maximum intensity, initial SWC, *React*, *RisT*  
685 and *Amp* were crossed in order to find out relationships allowing to better understand SWC  
686 dynamics at the event scale and among monitored land covers (Fig. 14). Three significant  
687 relationships emerged from this analysis. Mean rainfall intensity was inversely correlated to *React*  
688 and *RisT*. High mean rainfall intensity led to short reaction and short rising time whatever the

689 land cover. An expected correlation was observed between initial SWC and *Amp*. Low initial SWC  
690 induced higher SWC variations. However, this relationship was different according to the  
691 monitored land covers: SWC variations proved lower in forest than in grassland and black marl.  
692 Moreover, initial SWC ranged from 7% to 27% in black marl, from 13% to 32% in grassland, and  
693 from 22% to 41% in forest. From these observations, it can be concluded that soils under forest  
694 have a greater storage capacity (higher porosity) but drainage is better in soils under grassland  
695 (higher transmissivity).

696

697 **Fig. 14. Three significant relationships between rainfall properties and some SWC index (initial SWC, variation**  
698 **amplitude) at the plot scale and the event time scale.**

699

#### 700 **4.4.3 Subsurface flow processes**

701

702 98 *Smax* values were computed from the seven studied flood events (Fig. 15). Low *Smax*  
703 (< 1000) represented 45% of measured *Smax* and were mainly associated to November events.  
704 The frequency of low *Smax* increased from the beginning to the end of November according to  
705 the catchment wetting. Low *Smax* were almost equally observed in every monitored land cover  
706 with a higher number of observations in forest due to a higher number of monitored plots (6  
707 against 4 in black marl and 4 in grassland). The frequency of *Smax* between 1000 and 5000 was  
708 lower in forest and black marl than in grassland. High *Smax* (> 5000) were only measured during  
709 summer events and during the first fall event (October 14). *Smax* > 6000 were mainly measured in  
710 grassland.

711

712 Relationships between *Smax*, land cover and initial SWC are consistent with observations  
713 made in Fig. 4. High *Smax* were more often observed in grassland where the probes reacted more  
714 quickly to rainfall due to higher transmissivity of soils and to the limited impact of interception.

715 Conversely, low  $S_{max}$  were predominant in forest due to lower drainage capacity and high  
716 interception by trees.  $S_{max}$  observed in black marl were similar to the  $S_{max}$  in the forest although  
717 isolated observations of very high  $S_{max}$  were observed. Occurrence of subsurface flow in black  
718 marl is explained by the anisotropic nature of the material involving preferential lateral flow.

719

720 **Fig. 15. Frequency distribution of  $S_{max}$  calculated from all sensors at 15 cm depth. Left graph shows  $S_{max}$  frequency**  
721 **distribution by land cover. Right graph shows  $S_{max}$  frequency distribution by event.**

722

723

## 724 **5 Discussions**

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725

### 726 **5.1 Remarks on SWC measurements**

727

728 Detailed knowledge of SWC absolute values over the catchment would require a network of  
729 numerous probes that would entail high costs to install and to maintain in good conditions.  
730 Finally, a capacitance sensor network composed of a small number of low cost probes was  
731 suitable for studying SWC mean variation at daily, hourly and event time scales in the Laval  
732 catchment. This is supported by recent findings of Mälicke *et al.* (2020) who demonstrated (from  
733 a study in the 19.4 km<sup>2</sup> Colpach catchment) that a minimal number of SWC sensors could capture  
734 soil moisture dynamics at the catchment scale and explain its hydrological dynamic. Sensors  
735 location strategy is a key point in the purpose of estimating soil moisture mean status at the  
736 catchment scale. This strategy is usually based on identified soil-landscape units using different  
737 geostatistical methodologies (Corradini, 2014 ; Zhuo *et al.*, 2020). Backing up the existing probe  
738 network with other sensors to monitor SWC in the identified soil-landscape units elsewhere in the  
739 catchment could enhance the proposed methodology by validating mean porosity values  
740 measured among land covers to characterize SWC more accurately. Eventually,  $S_{max}$  analysis

741 would have been enhanced if SWC data obtained by the same sensors at multiple depths were  
742 available.

743

744 Extreme SWC values (dry or wet) are a key point impacting soil water exchanges (Teuling *et*  
745 *al.*, 2006). Mittlebach *et al.* (2011) showed that accuracy measurement of 10HS sensor decreases  
746 with increased SWC, which results in overestimation at low SWC and underestimation at high  
747 SWC (> 40%) especially in clay soils. Extreme SWC values measured by 10HS in the Laval  
748 catchment (values corrected by field-calibration) were near 0% but never exceeded 40% in black  
749 marl, whereas they were never less than 12% and regularly exceeded 40% in forest and grassland  
750 at the event time scale. It is well known that SWC capacitance sensor accuracy depends on the  
751 effect of the monitored soil properties on site-specific calibration. On this basis, a specific effort  
752 must be made to reduce measurement errors, especially for extreme high values. Mittlebach *et*  
753 *al.* (2011) showed that specific site-calibration of the 10HS sensor can help reduce measurement  
754 error to 2% (with error values ranging from -7% to 3% in loamy soils and from -8% to 5% in clayey  
755 soils). In the Laval catchment, the forest field-site calibration was similar to the manufacturer's  
756 calibration, whereas the field-site calibration was different in grassland and black marl. The field-  
757 site calibration reduced the 10HS sensor mean measurement error from 12% to 3% in grassland  
758 and from 11% to 4% in black marl. It is assumed that a 4% mean measurement error is reasonable  
759 for estimating mean SWC patterns at the catchment scale. Moreover, estimated SWC values in  
760 the investigated and validation plots were primarily less than measurement error.

761

## 762 **5.2 Explanatory variables and SWC estimation**

763

764 The five variables used in the geostatistical model were appropriate for estimating SWC at  
765 the catchment scale. Regarding relationships between some of these variables, questions about  
766 the impact of each variable in the geostatistical model could be asked. What impact if only NDVI

767 and soil depth were used to run the model? Different combinations from 2 to 5 variables were  
768 tested. The difference in estimated SWC using two variables (mean  $R^2 = 0.84$ ) and five variables  
769 ( $R^2 = 0.88$ ) was very low. But except for curvature index, each variable enhanced the SWC  
770 estimation during rainfall periods. However, these variables give a simplified understanding of  
771 SWC variation at the catchment scale. Using soil properties could help explain SWC variation at  
772 the event time scale. Indeed, regolith type, thickness, dip orientation, porosity, and soil infiltration  
773 capacity are parameters that affect SWC and runoff generation at the hillslope scale, which  
774 contribute to the hydrological complexity of badlands (Kuhn *et al.*, 2004). But at present time it  
775 was not possible to properly map these data.

776

777 Finally, model uncertainties can be attributed to the low number of measurement plots  
778 and the high natural heterogeneity of SWC in a mountainous and steep environment. Even if the  
779 model takes into account local variables that affect SWC at the plot scale, estimated values at  
780 unmeasured plots are influenced by SWC values of the nearest measured plots (Lhottelier, 2006).

781

### 782 **5.3 Impact of the catchment hydric status, geomorphology and landuse on SWC-runoff thresholds and** 783 **SWC space-time variability**

784

785 In dry period, peakflow measured in the Laval resulted mainly from hortonian runoff and  
786 occurred before peak SWC. In wet period, higher subsurface flow occurrence resulted in an earlier  
787 reaction of SWC than streamflow. These delays between max SWC and peakflow are similar to  
788 what Penna *et al.* (2011) observed in the 1.9 km<sup>2</sup> mountainous Rio Vauz catchment (elevations  
789 ranging from 1835 m to 3152 m) mainly composed of Dolomitic rock cliffs, steep slopes and a  
790 valley bottom covered by Quaternary till. These results highlight a reproducibility of soil  
791 hydrological processes despite various land uses and geomorphology. At the seasonal scale, Fan  
792 *et al.* (2020) observed in a 0.08 km<sup>2</sup> forested catchment in Pennsylvania (USA) dominated by a

793 humid continental climate that SWC was spatially more variable but temporally more stable  
794 during wet cold season compared to dry warm season. Observations made in the Laval are  
795 different since the Mediterranean climate is very contrasted with a long dry period with rare,  
796 short and intense storms while the wet period has a temporally heterogeneous distribution of  
797 long and high cumulative rainfalls. Recharge and drainage phases are then easily identified  
798 regarding to SWC spatial and temporal dynamic.

799

800 In terms of hillslope morphology, Moore *et al.* (1998) observed in a 0.075 km<sup>2</sup> gully  
801 catchment located in New South Wales (Australia) that topographic nonuniformity within small  
802 catchments controlled SWC spatial variability and the location of ephemeral gullies. They showed  
803 that dry near-surface soils were quite propitious to gullies development. Similar observations  
804 were made in the Laval catchment which also has a very dense gully network located on bare  
805 areas (Thommeret, 2012). In the Laval the deepest and most durable gullies are located at the  
806 bottom of concave hillslopes where near-surface SWC is greater than SWC measured at upslope  
807 and mid-slope areas which are more propitious to ephemeral gullies whatever the slope shape. In  
808 a 0.56 km<sup>2</sup> agricultural (essentially wheat) and semi-arid catchment located in Eastern Colorado  
809 (USA), Green and Erskine (2011) showed that vertical processes appeared to control SWC profile  
810 dynamics at summit positions while infrequent overland flow and unsaturated subsurface lateral  
811 flow appeared to control SWC dynamics at downslope positions. Subsurface lateral flow type is  
812 also dominant downslope in the Laval catchment whatever the land use. However, situations is  
813 quite different at summit and mid-slope in black marl areas regarding to the variability of soil  
814 hydraulic conductivity values, material anisotropy and rainfall intensity (Estèves *et al.*, 2005).  
815 Thus, summit are more associated to overland flow type while water is transported from summit  
816 to hillslope bottom by a combination of overland and lateral subsurface flow processes.

817

818

## 819 6 Conclusions and outlook

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820

821 This study showed that mean SWC dynamics can be related to specific soil-vegetation  
822 patterns in badlands and that it is possible to distinguish SWC signatures among land covers.  
823 Geostatistical modeling using a small number of geographical variables makes it possible to  
824 estimate SWC at the plot scale and at daily and hourly time steps. These geographical variables  
825 are useful to predict wetness/dryness status at the catchment scale apart from flash flood events.  
826 However, it is not possible to determine the impact of these variables on the studied land covers  
827 separately. At the event scale, SWC dynamic analysis (*S<sub>max</sub>* index) made it possible to show that  
828 matrix flow would be associated to long autumn rainfall with low intensity producing low outflow  
829 ( $Q_{max} < 1500$  l/s) and would appear in every land covers (Fig. 16). While preferential flows would  
830 be caused by summer storm with high rainfall intensity giving birth to large flood such as the  
831 October 14 event ( $Q_{max} = 10\ 000$  l/s) and would be more often observed in grassland.

832

833

834 **Fig. 16. Relationships between SWC measurement time steps, variables determining SWC, hydrological processes and**  
835 **land covers.**

836

837 Future work will focus on validating this methodology by modeling hydrological processes  
838 with a physically-based model that integrates climate forcing especially on surface runoff.  
839 Regarding to high SWC variations it is assumed that black marls area have a major contribution to  
840 stream flows whereas water stored in grassland and especially in forests where soils are deeper is  
841 primarily lost for runoff. The goal of the future work will be to assess independently the impact of  
842 the areal distribution of SWC on runoff generation.

843

844

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846

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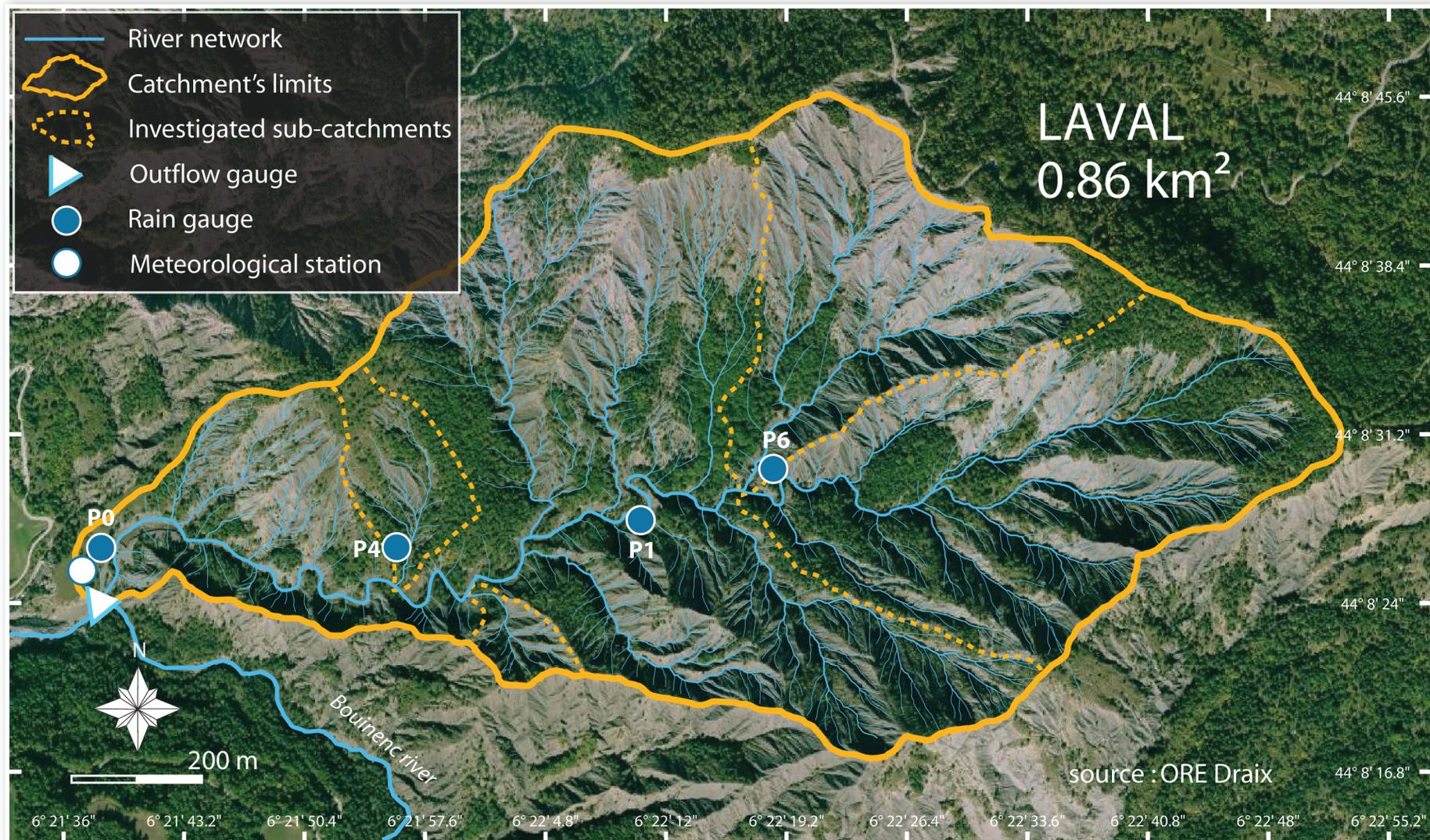
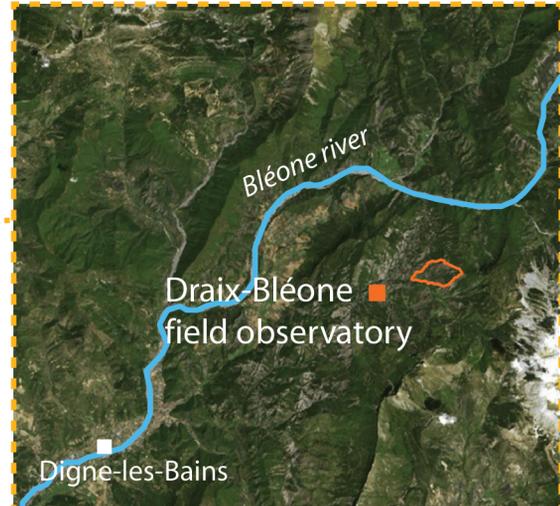
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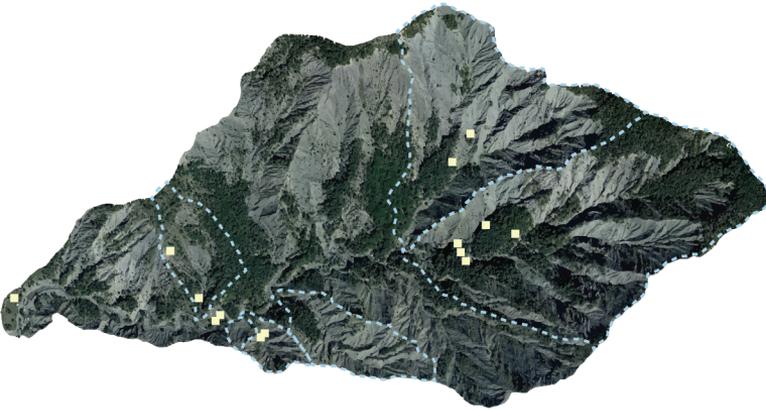
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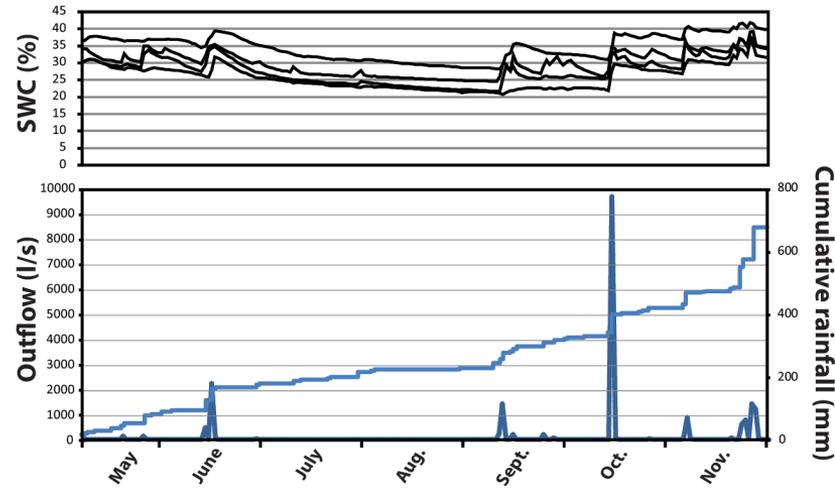
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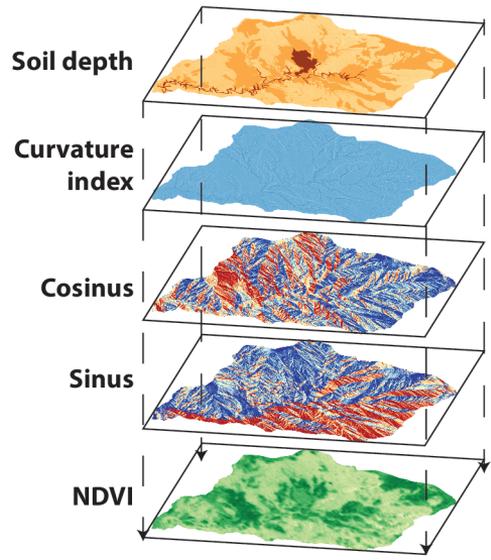
# 1/ Capacitance sensors network design, setup and calibration



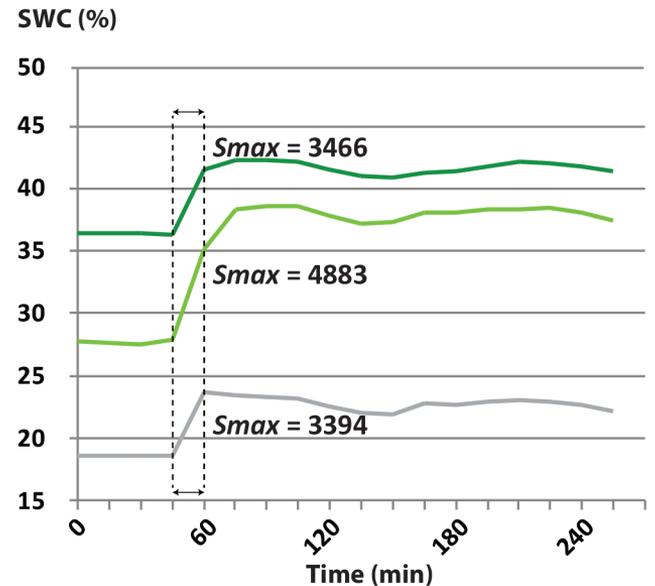
# 2/ SWC, rainfall and outflow monitoring



# 3/ SWC estimation using spatial interpolation based on geographical variables

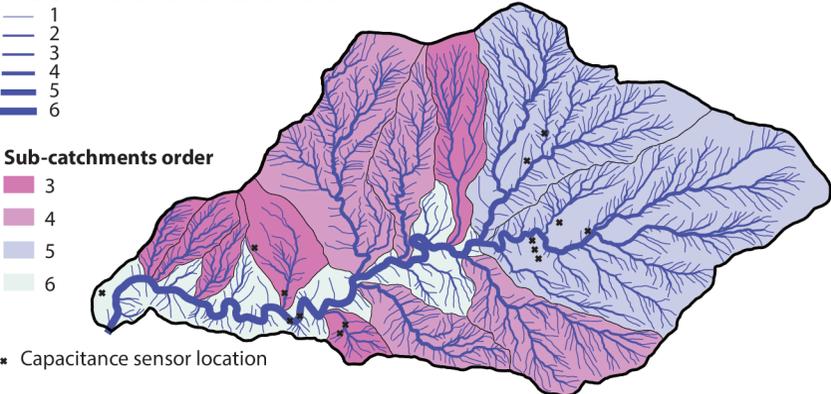


# 4/ Identifying the dominant flow mechanism from the wetting curve maximum slope method



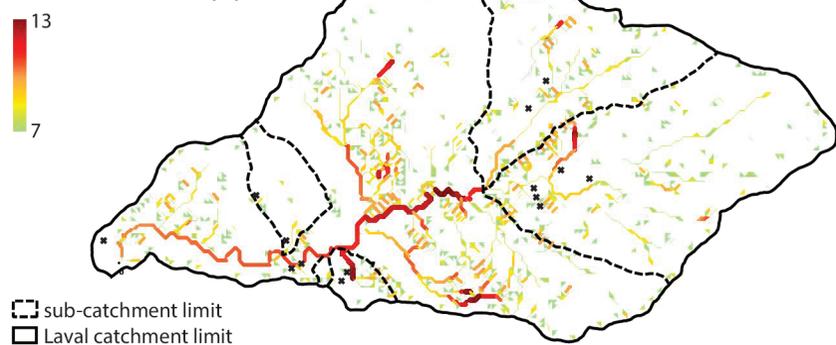
# 1/ Sub-catchments classification

## Strahler river network classification



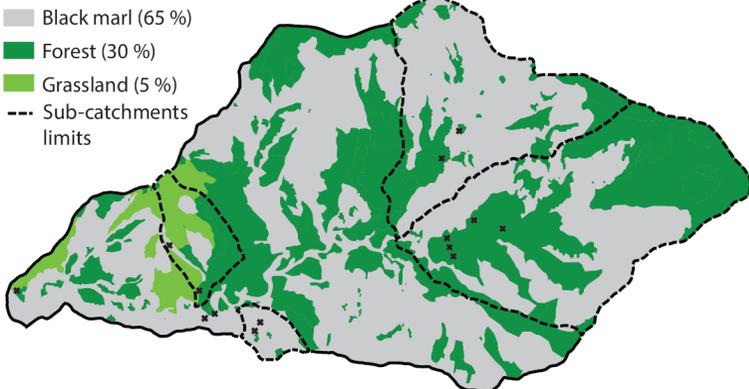
# 2/ Identification of theoretical surface flow concentration areas

## Concentration index (CI)



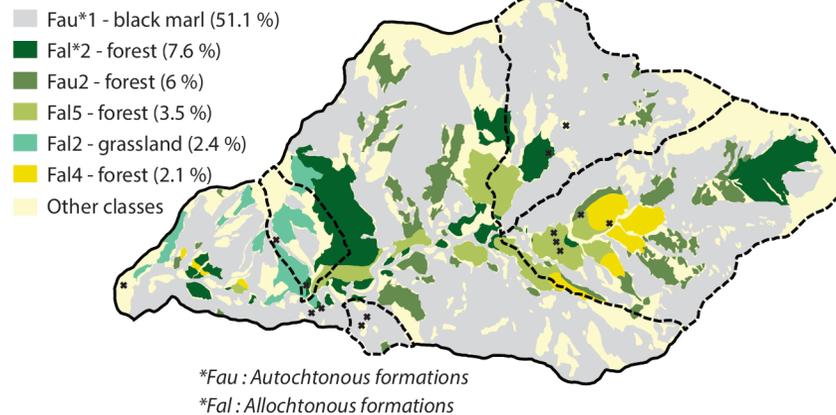
# 3/ Selection of 4 sub-catchments based on land uses

## Main land cover (proportion of the Laval surface)



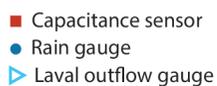
# 4/ Soil-vegetation map

## Main soil-vegetation pattern (75 % of the Laval surface)

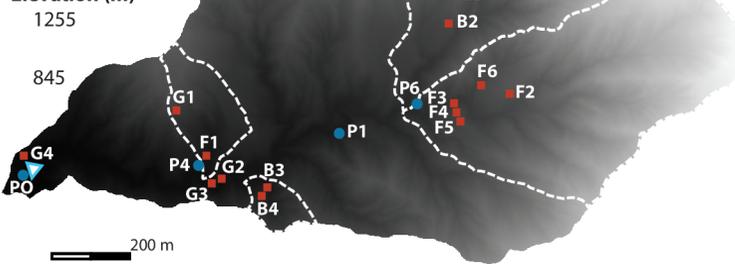


# 5/ SWC monitoring network

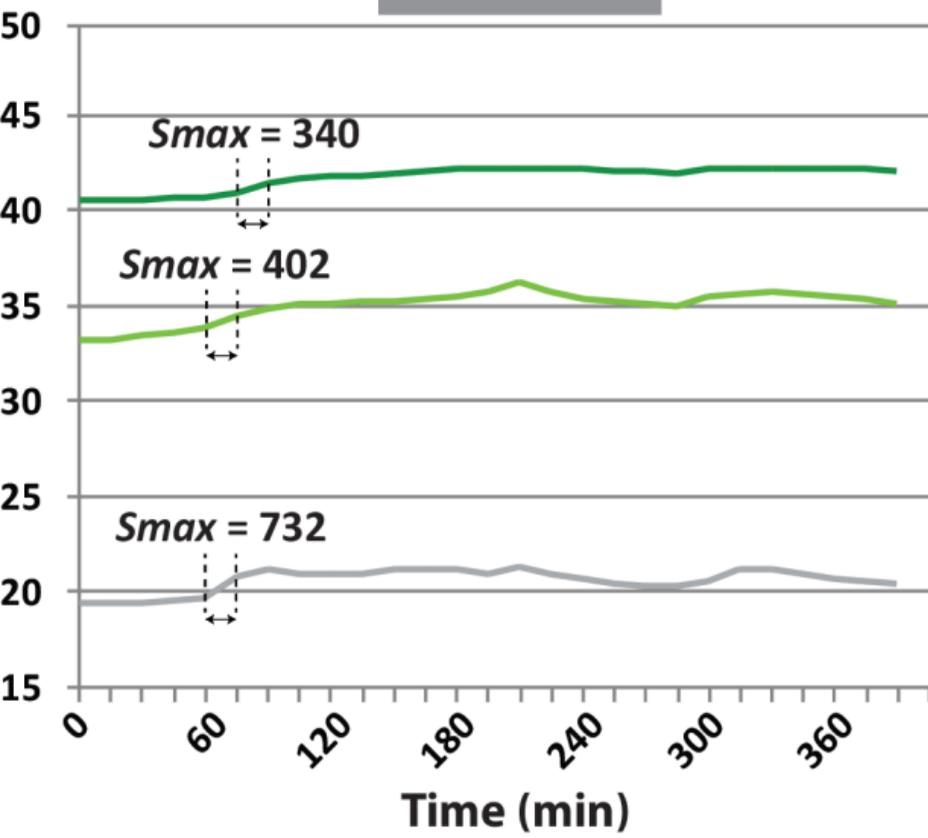
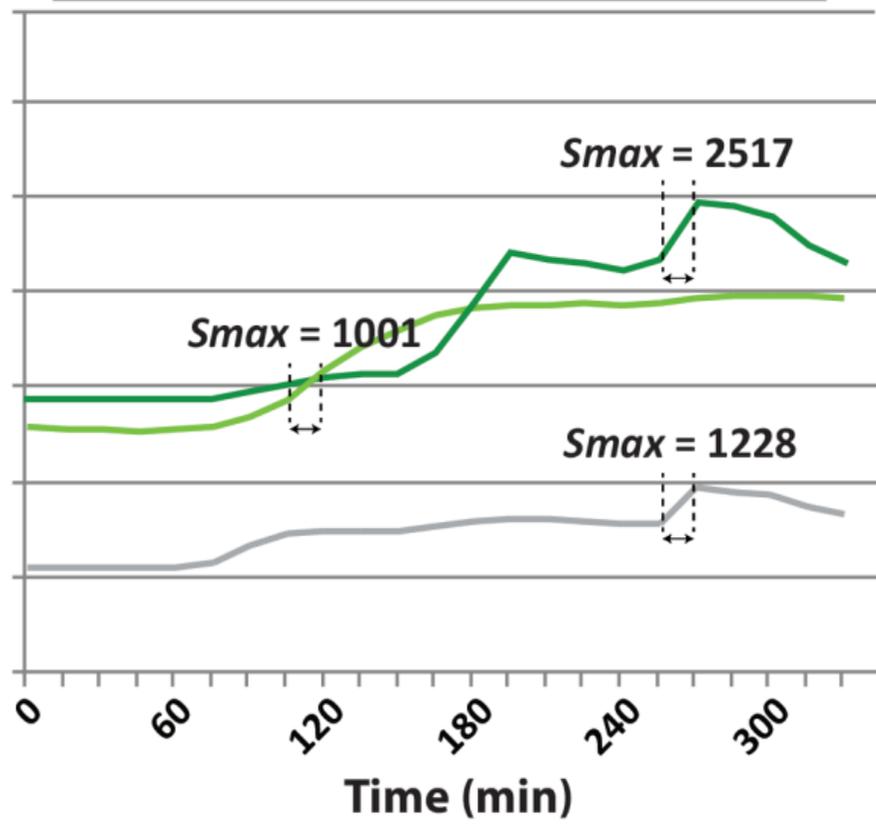
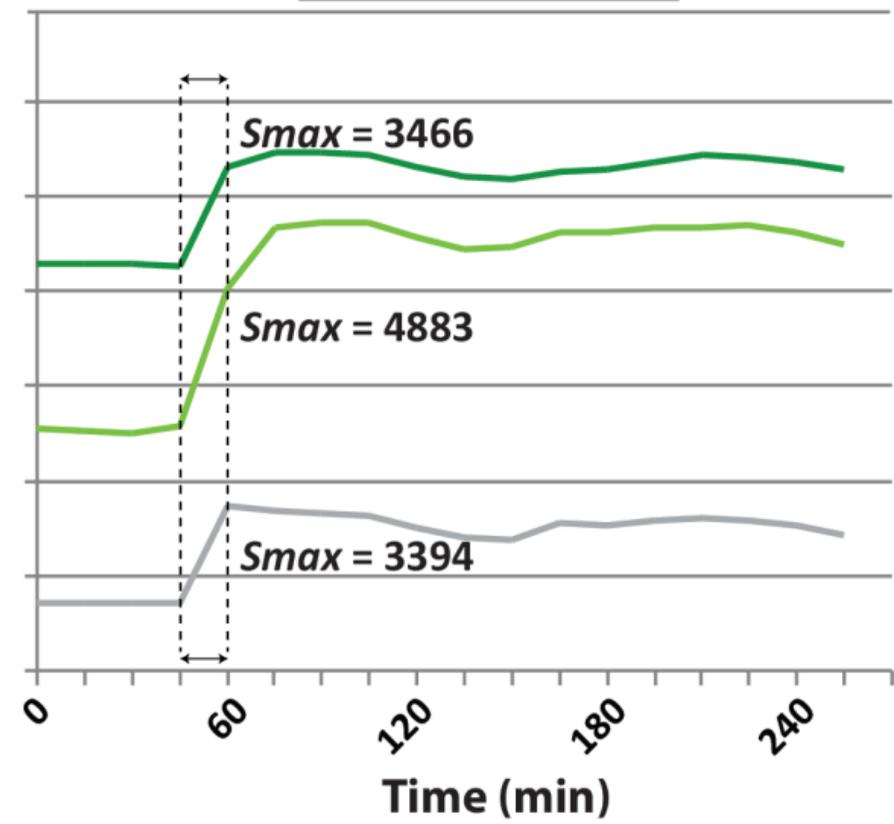
## Setup



## Elevation (m)



SWC (%)

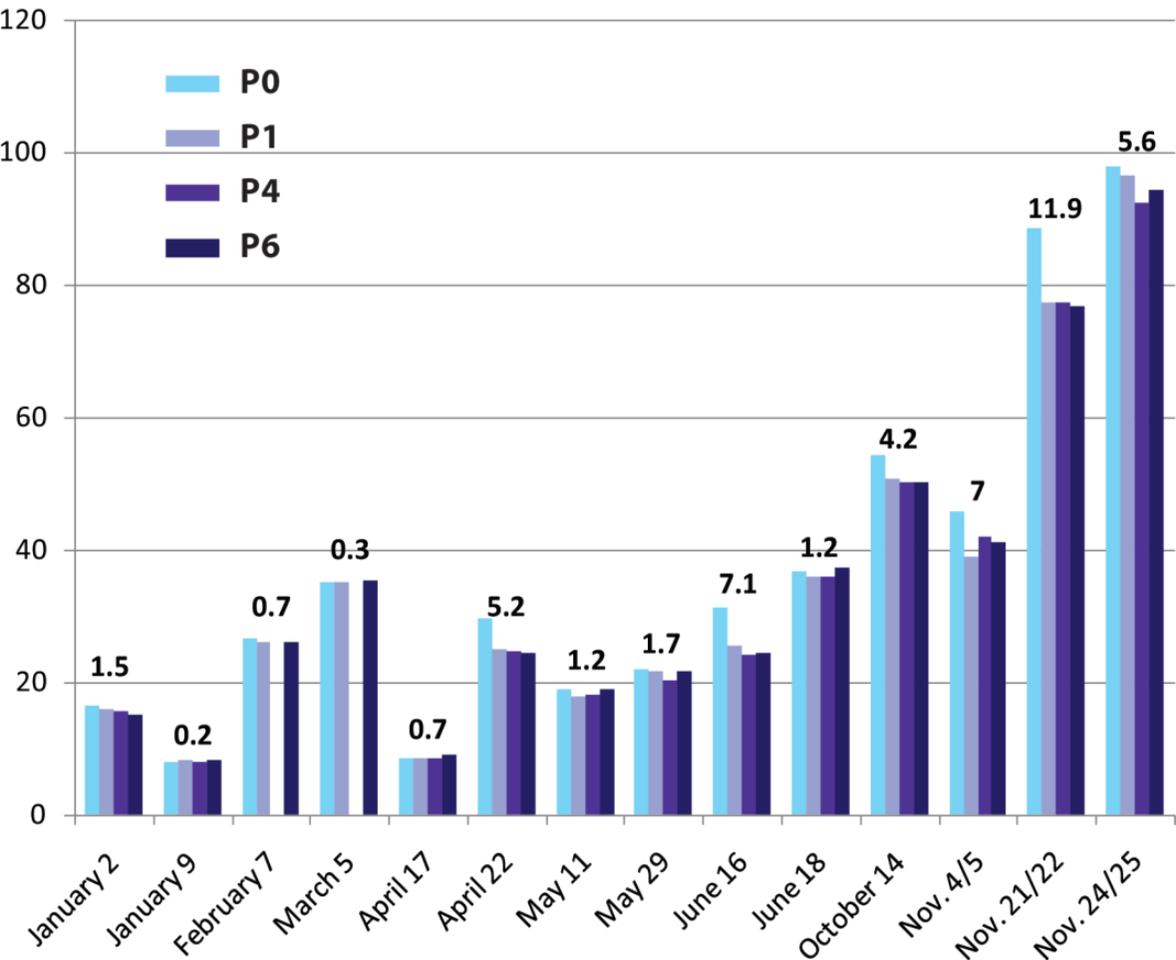
*Matrix flow**Mix of matrix and preferential flows**Preferential flow*

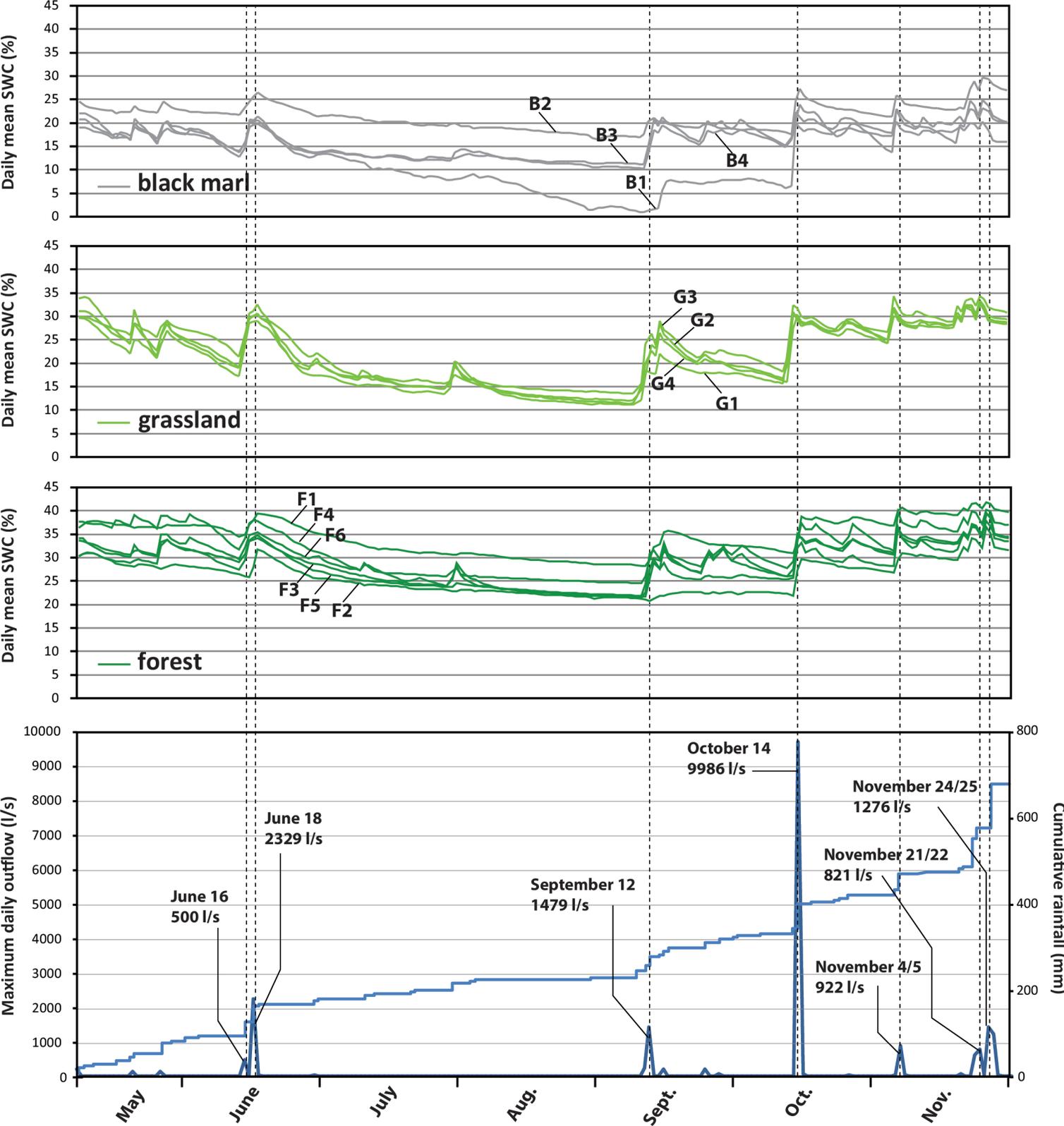
— black marl

— grassland

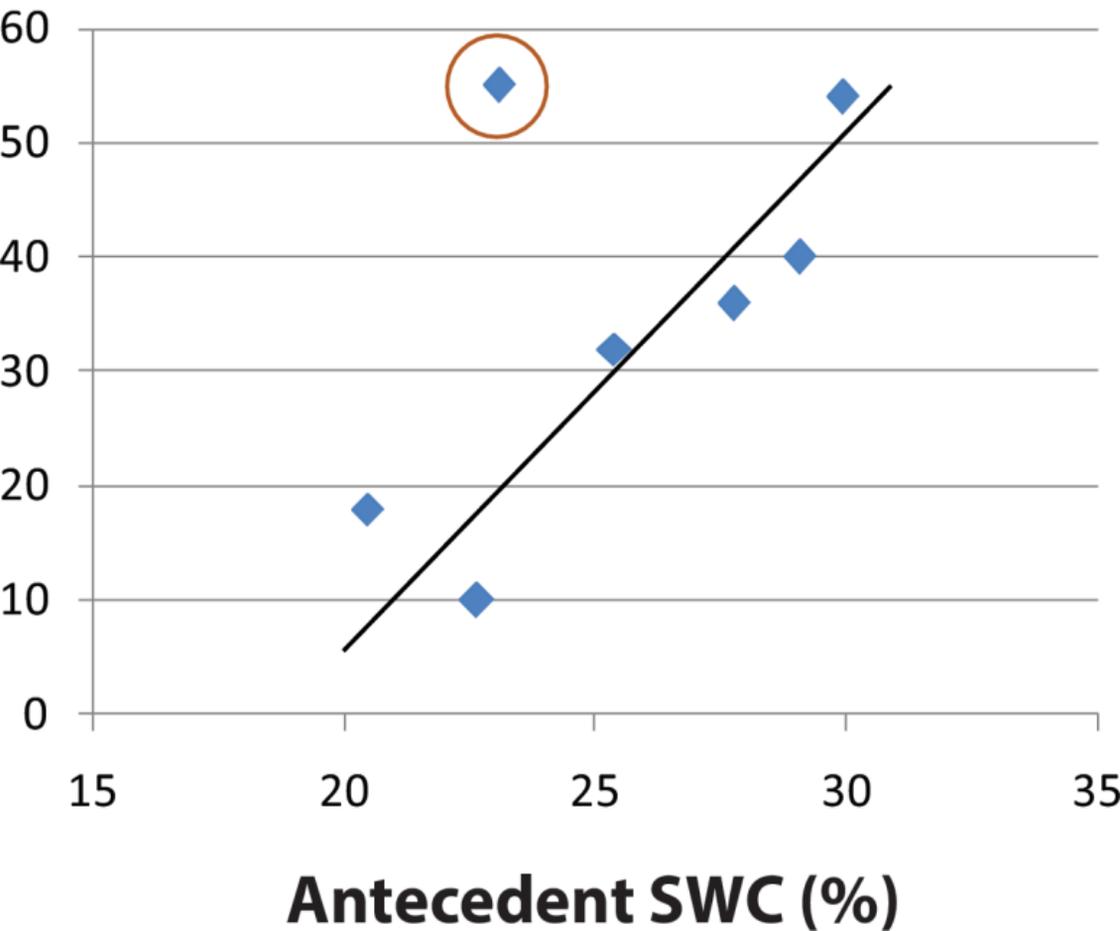
— forest

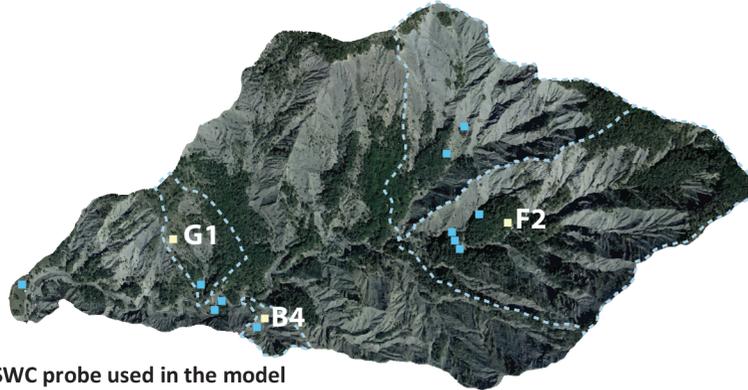
# Rainfall (mm)



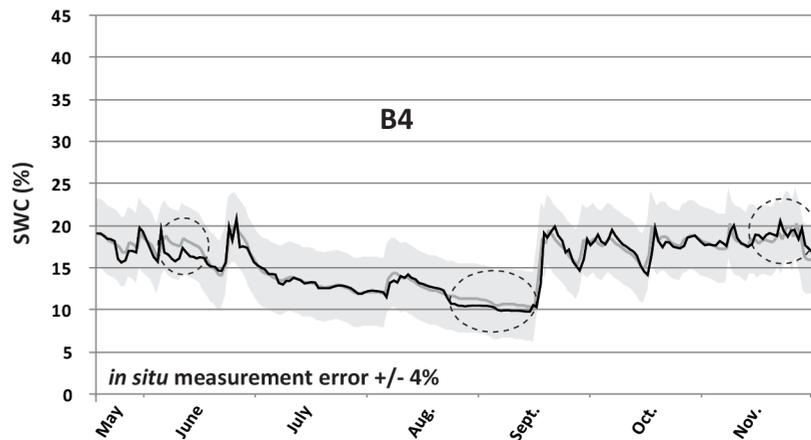
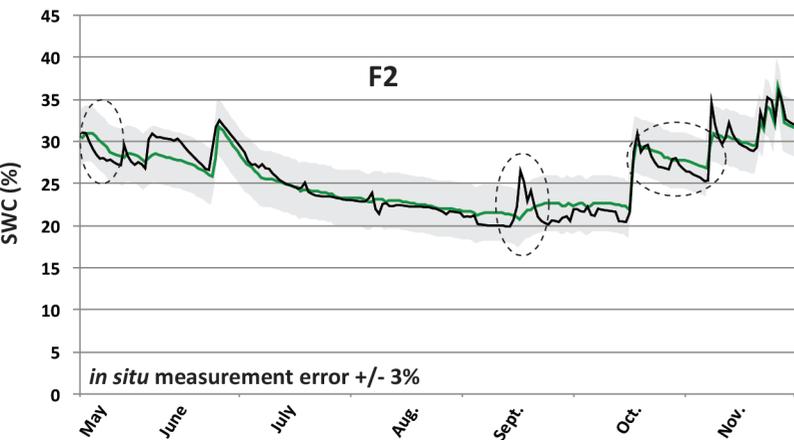
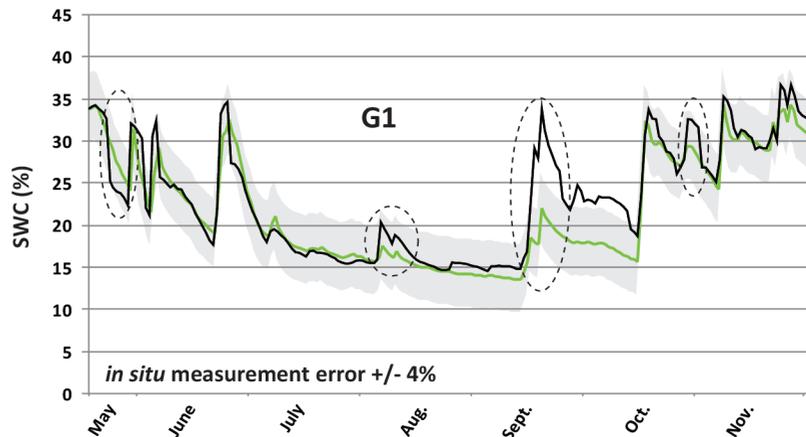


# Runoff coefficient (%)



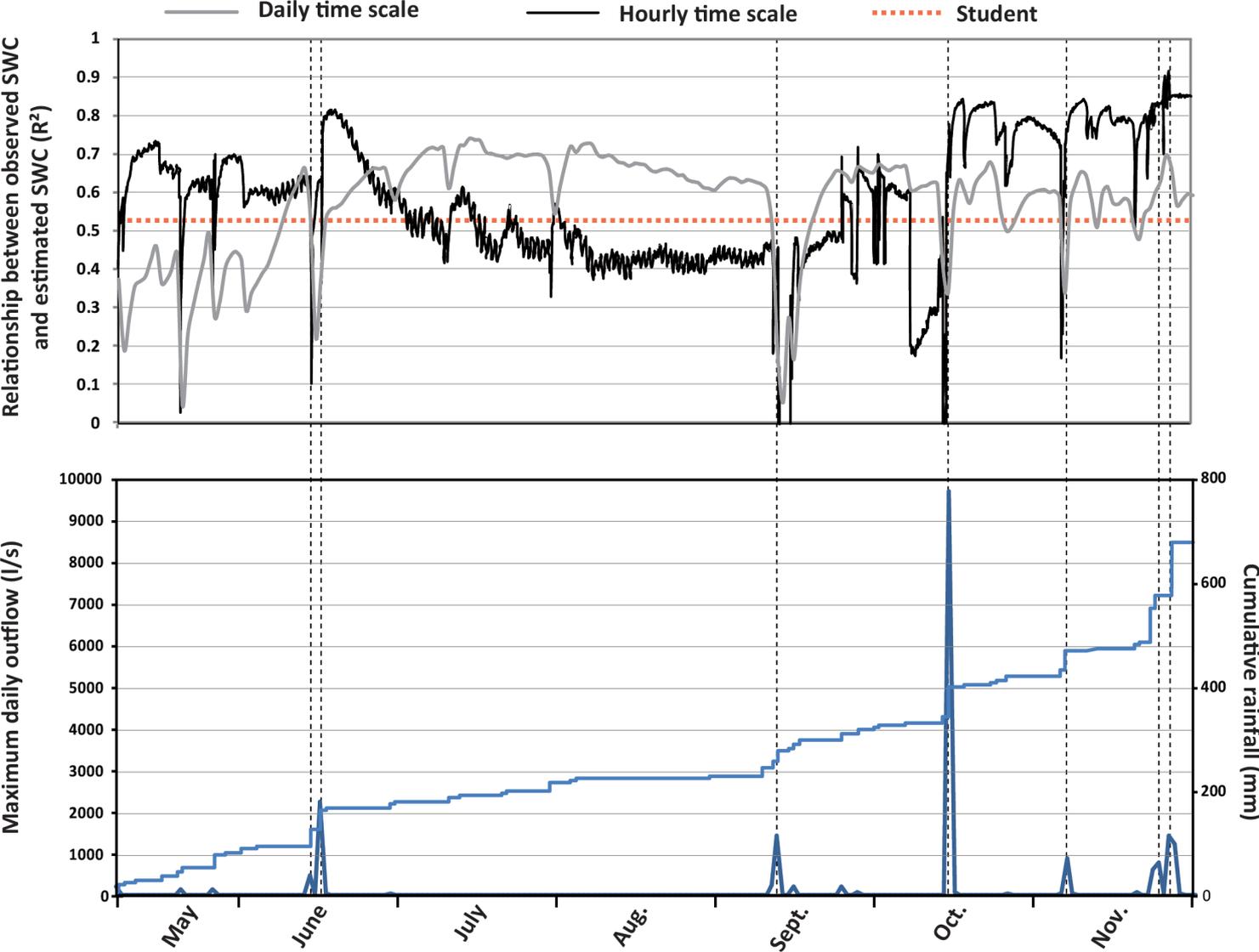


- SWC probe used in the model
- SWC probe used for model validation



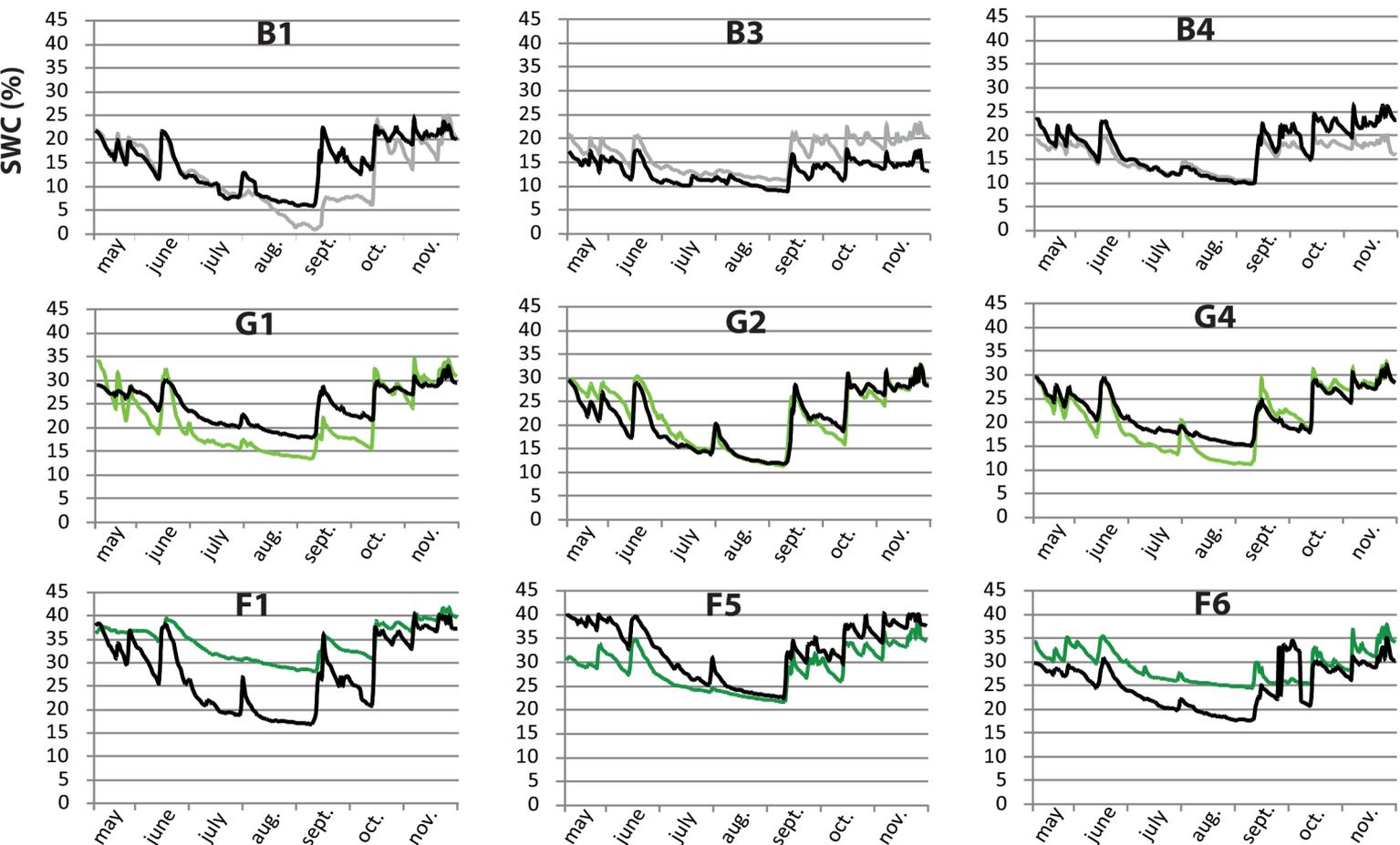
- SWC measured in black marl
- SWC measured in grassland
- SWC measured in forest

- Estimated SWC
- In situ measurement error
- Main overestimations and underestimations



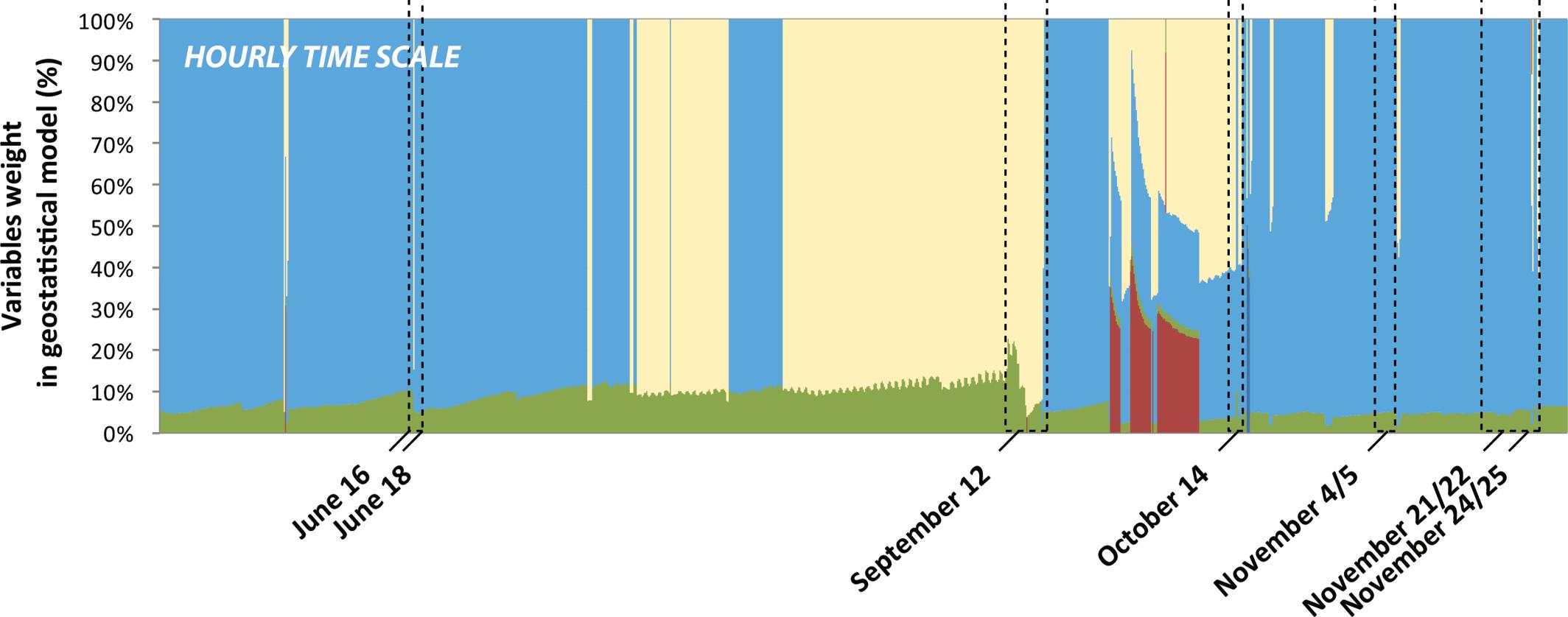
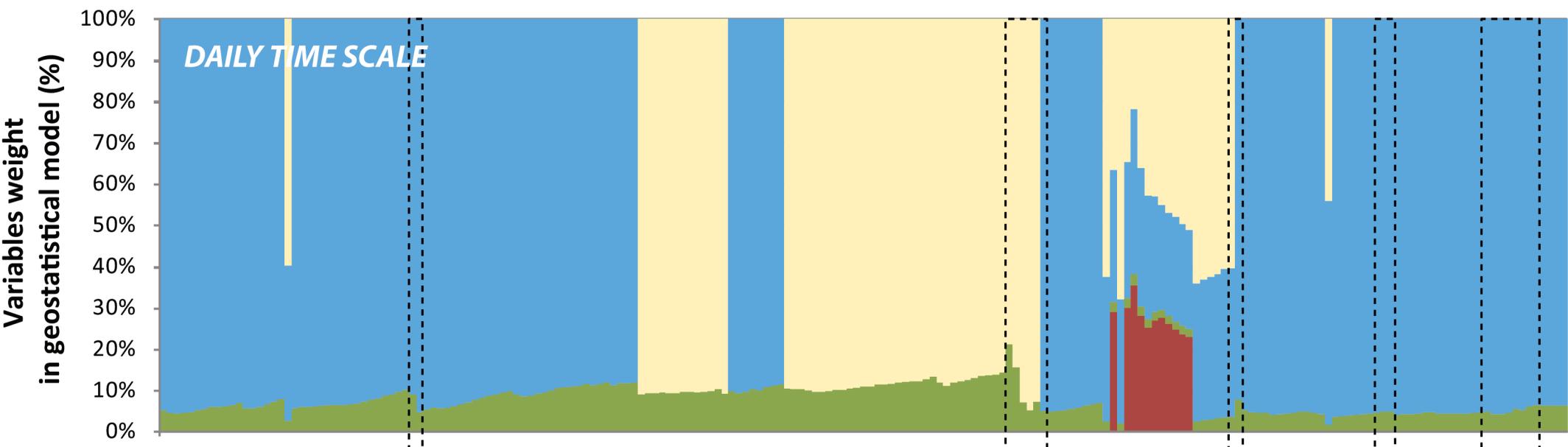
# Relationship between measured and estimated SWC ( $R^2$ )

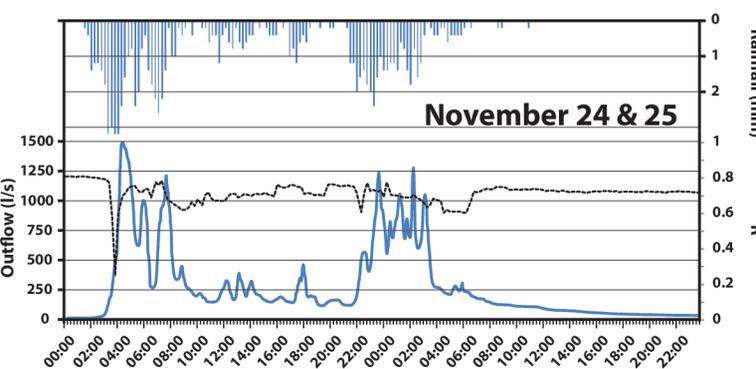
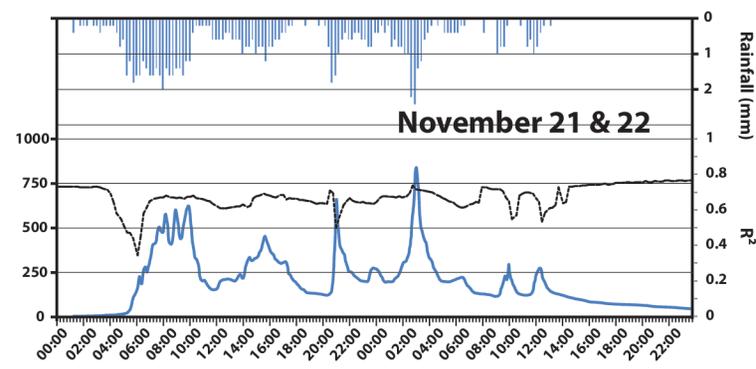
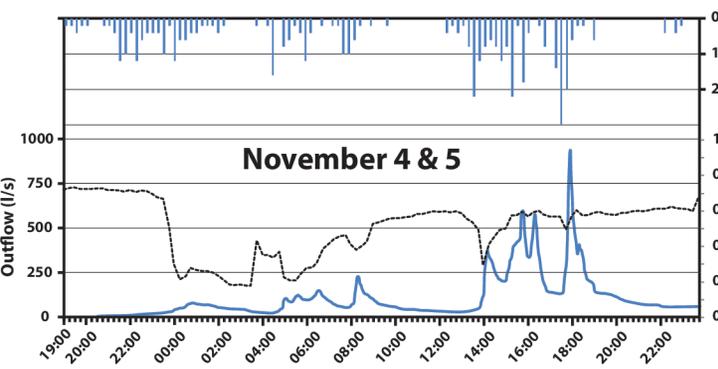
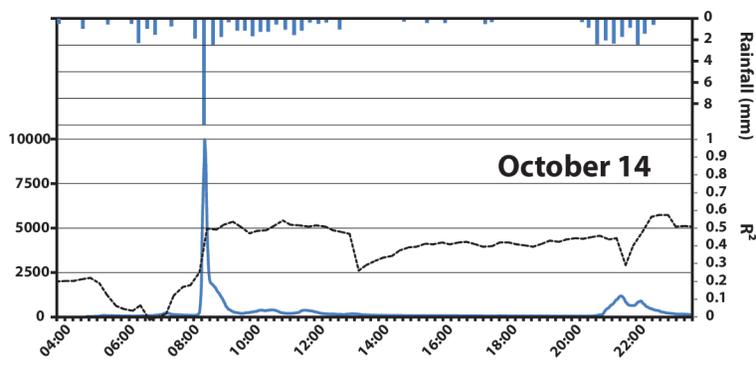
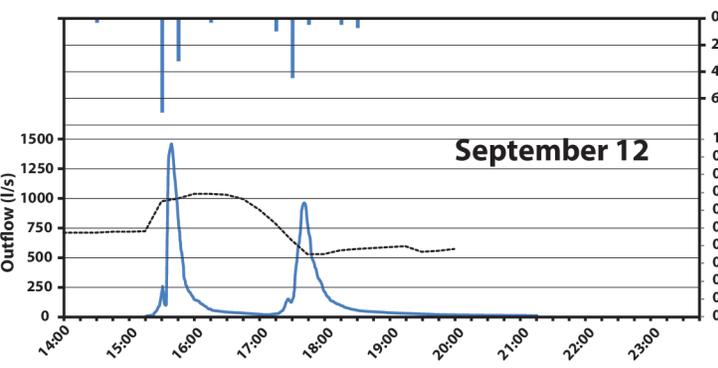
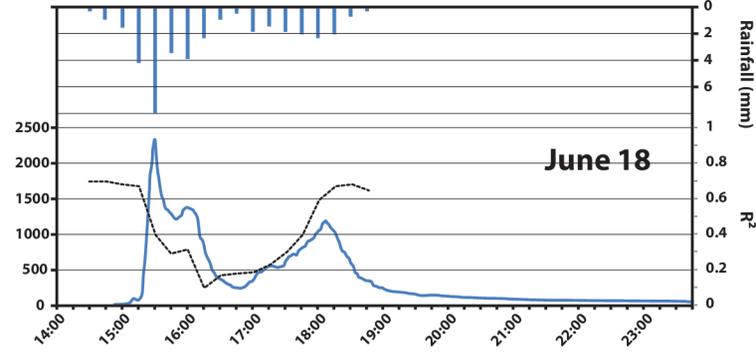
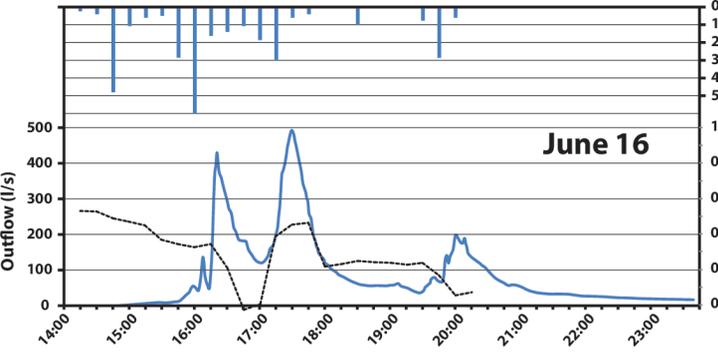
	B1	B2	B3	B4	G1	G2	G3	G4	F1	F2	F3	F4	F5	F6
Daily time scale	0.394	0.533	0.932	0.889	0.189	0.996	0.995	0.692	0.607	0.802	0.886	0.952	0.861	0.528
Hourly time scale	0.393	0.515	0.933	0.884	0.167	0.996	0.995	0.691	0.605	0.782	0.881	0.949	0.859	0.529



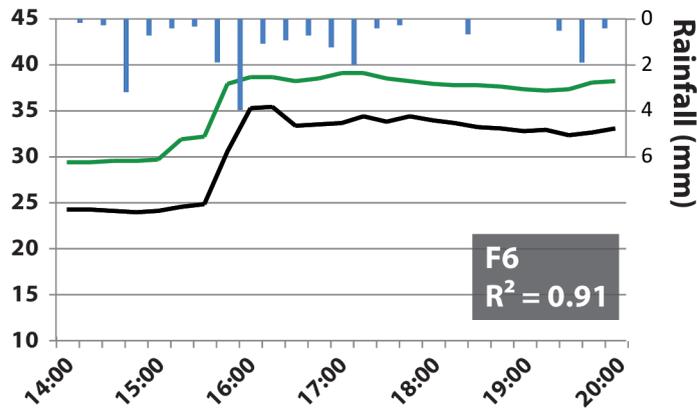
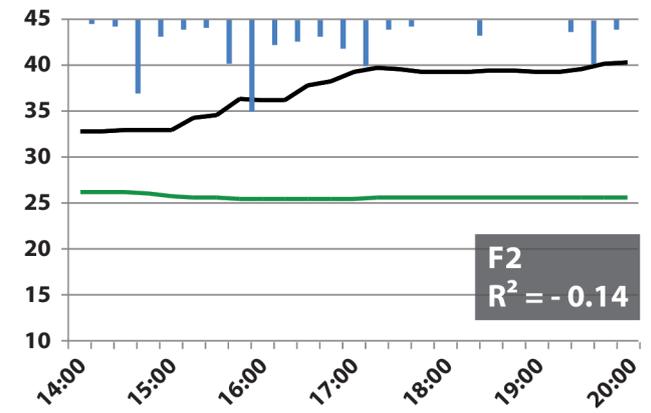
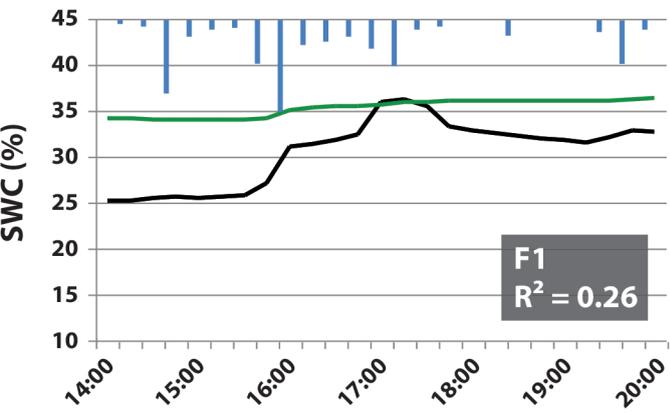
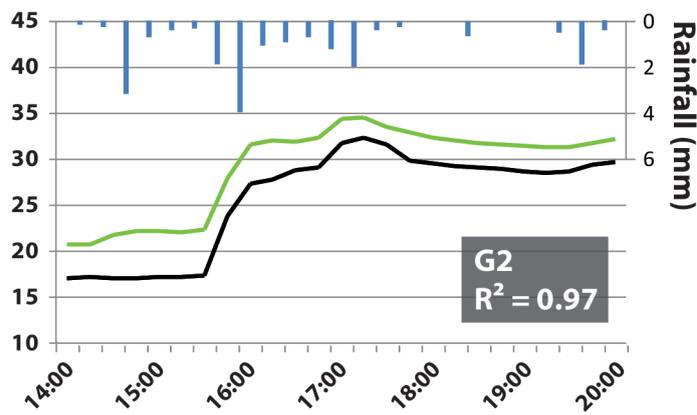
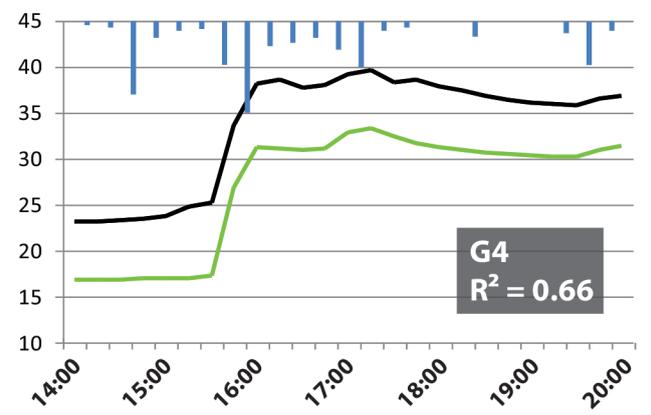
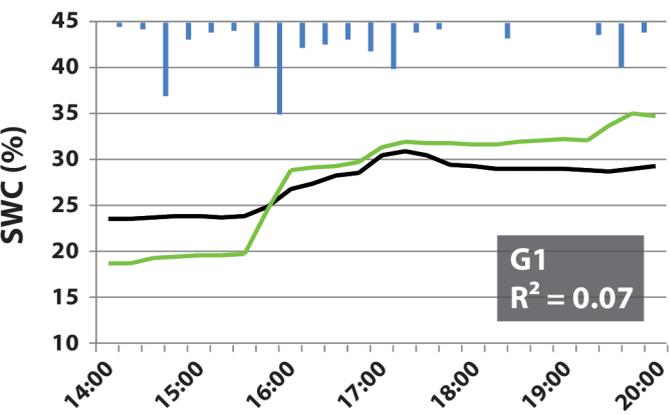
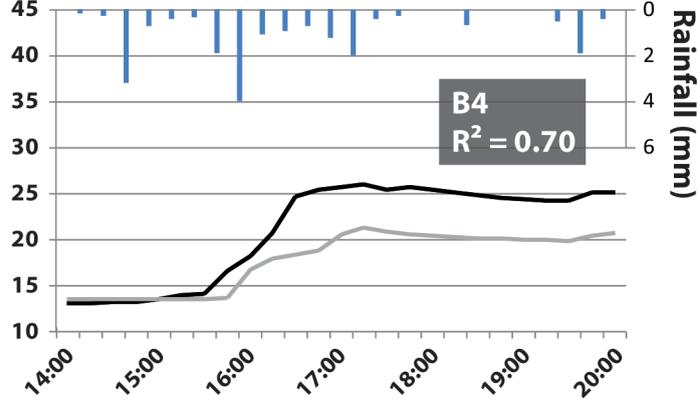
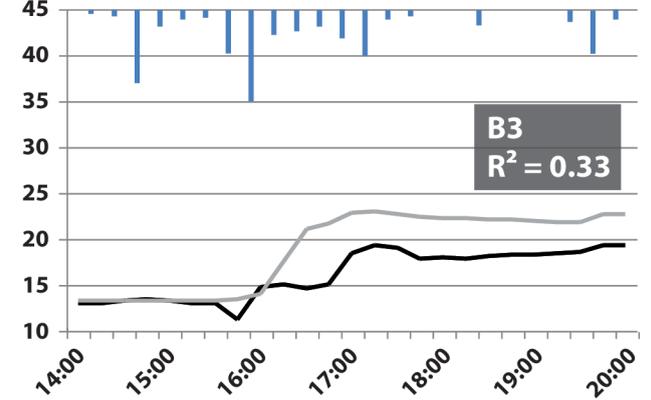
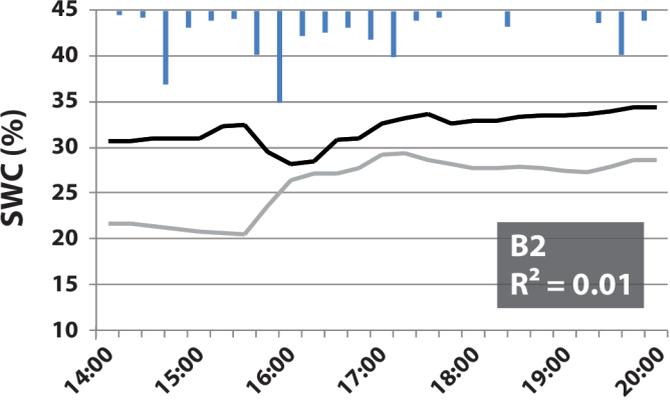
— SWC measured in black marl     
 — SWC measured in grassland     
 — SWC measured in forest     
 — estimated SWC

Soil depth    Curvature index    NDVI    Cosinus    Sinus    Rainfall period





----- Relationship ( $R^2$ ) between observed SWC and estimated SWC

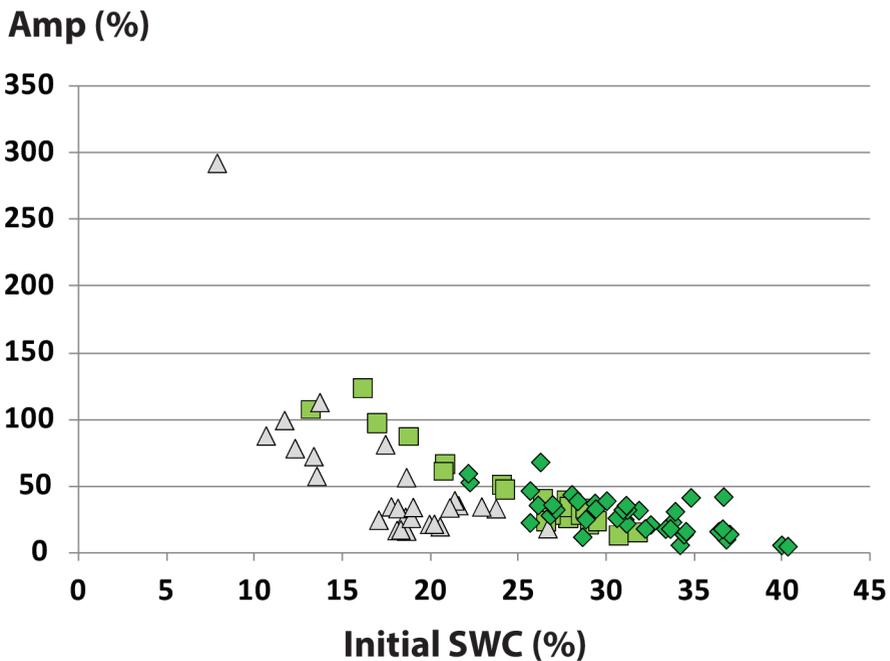
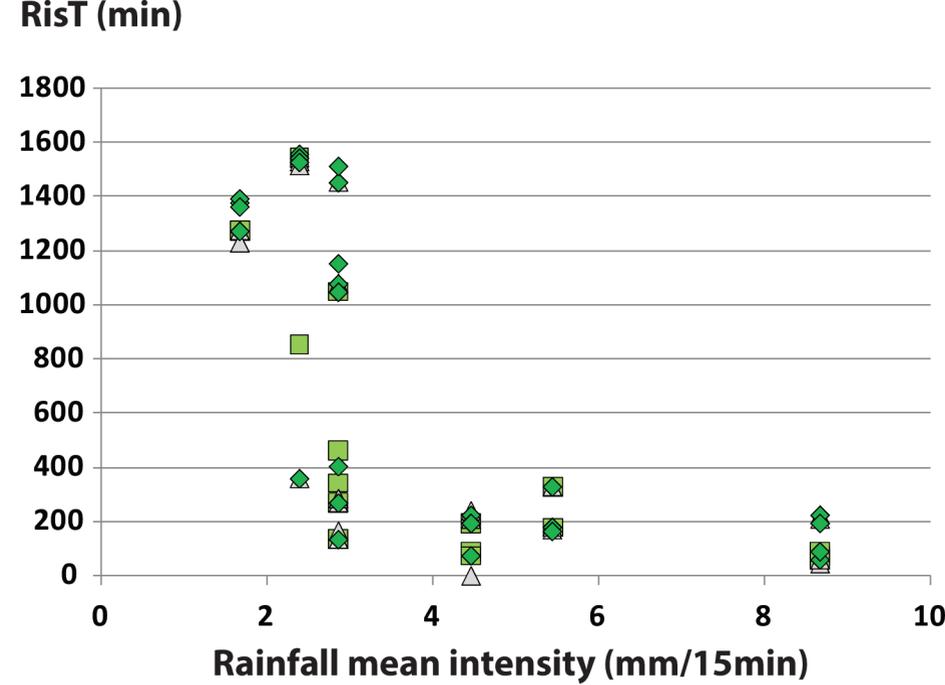
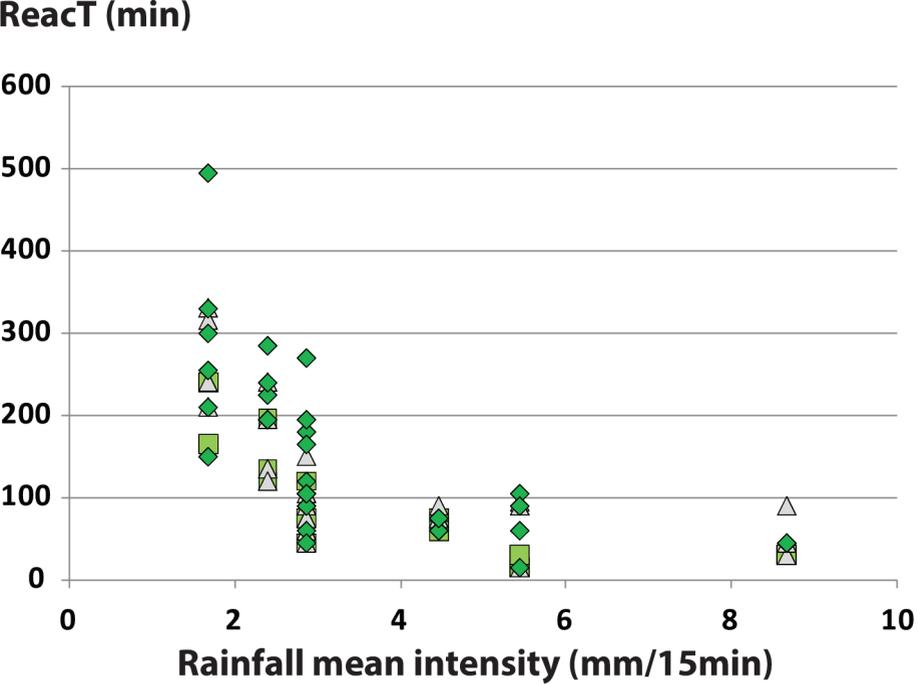


— SWC measured  
in black marl

— SWC measured  
in grassland

— SWC measured  
in forest

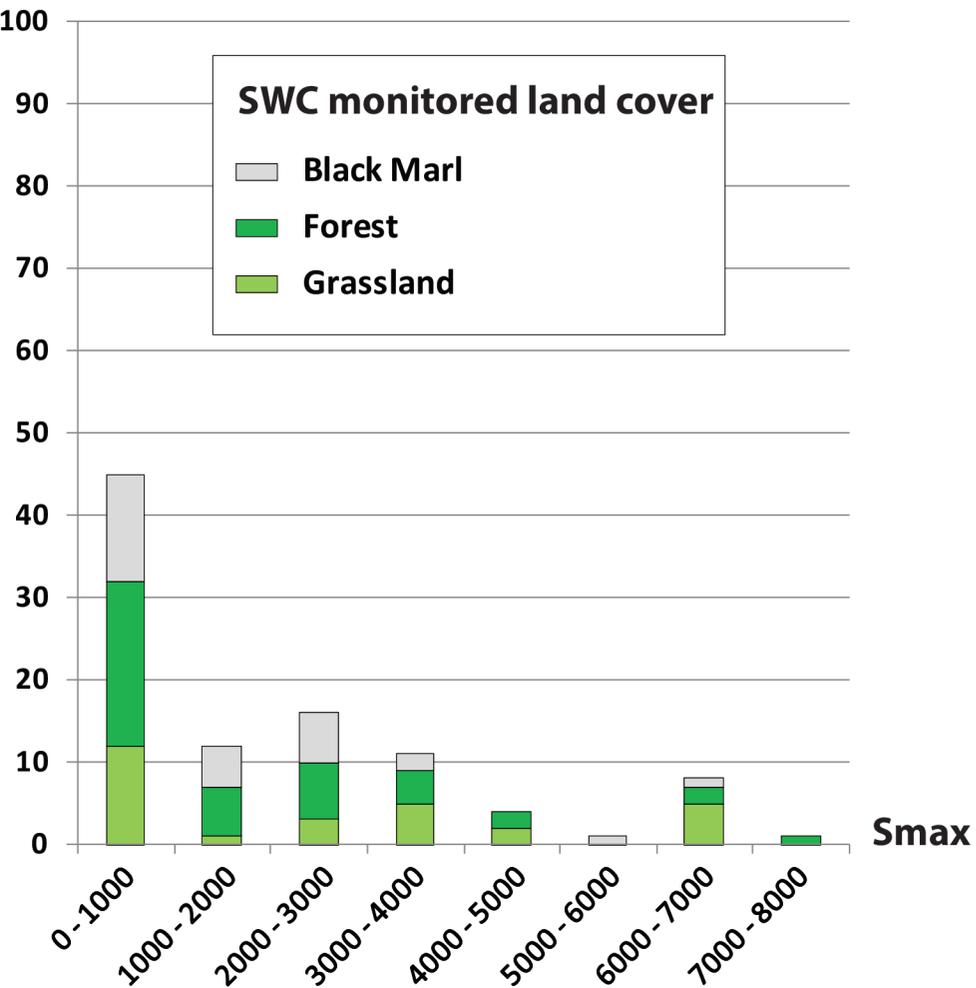
— estimated SWC



### SWC monitored land cover

- Black Marl
- Forest
- Grassland

Smax frequency (%)



Smax frequency (%)

