Event controls on intermittent streamflow in a temperate climate

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Abstract. Intermittent streams represent a substantial part of the total stream network and their occurrence is expected to increase due to climate change. Thus, it is of high relevance to provide detailed information of the temporal and spatial controls of streamflow intermittency to support management decisions. This study presents an event-based analysis of streamflow responses in intermittent streams in a meso-scale catchment with a temperate climate. ~~According to~~ the streamflow responses, precipitation events were classified into flow or no-flow classes. Response controls like precipitation, soil moisture, and temperature were used as predictors in a random forest model to identify the temporally changing factors that explain ~~of~~ streamflow intermittency at the event-scale. Soil moisture was the most important predictor ~~in the catchment~~, but the predictor importance varied ~~among the three dominant~~ geologi~~es, in the catchment.~~ Streamflow responses in the slate geology were controlled by soil moisture in the shallow and deep soil layers, while streamflow in the marl geology was primarily controlled by soil moisture in the upper soil layer. Streamflow responses in catchments underlain by both marls and sandstone were dependent on soil moisture whereas streamflow in the only catchment with a pure sandstone geology depended on precipitation characteristics. In all slate and marl catchments, streamflow intermittency varied also with soil temperature, which is probably a proxy- for seasonal changes in evapotranspiration ~~as well as~~ an indicator of freezing conditions.

1. Introduction

The scientific literature contains a variety of terms to define the different degrees of ~~stream~~flow intermittency for streams that cease to flow during certain parts of the year, including temporary, ephemeral, seasonal and episodic streams, and intermittent rivers (Uys and O'Keeffe, 1997; Costigan et al., 2016; Datry et al., 2017; Fritz et al. 2020). The stream network changes its spatial extent with the wetting and drying of these intermittent and ephemeral reaches. Even larger perennial rivers are becoming intermittent as a result of climate change and the number~~s are~~ expected to increase in the future (Datry et al., 2014; Reynolds et al., 2015). Climate, geology, soil, topography, and land use have been identified as major spatial controls of ~~stream~~flow intermittency (Olson and Brouillette, 2006; Reynolds et al., 2015; Trancoso et al., 2016; Costigan et al., 2016; Zimmer and McGlynn, 2017; Ward et al., 2018; Jaeger et al., 2019; Gutiérrez-Jurado et al., 2019; 2021; Prancevic and Kirchner, 2019; Kaplan et al., 2020a). The temporal dynamics of streamflow ~~were shown to~~ result from fluctuating contributions of groundwater ~~flow~~ and storm-flow depend~~ing~~ on the antecedent wetness state of the catchment (e.g. Zehe et al., 2007, Zimmermann et al., 2014; Jaeger et al., 2019). This study follows the definition of Busch et al. (2020)who define intermittent river~~s~~ as “a non-perennial river or stream with a considerable connection to the groundwater table, having variable cycles of wetting and flow cessation, and with flow that is sustained longer than a single storm event. These waterways are hydrologically gaining the majority of the time when considering long term flow patterns”. Accordingly, ephemeral stream~~s~~ ~~are~~ defined as “a type of non-perennial river or stream without a considerable groundwater connection that flow~~s~~ for a short period of time, typically only after precipitation events. These waterways are hydrologically losing the majority of the time when considering long term flow patterns” (Busch et al., 2020). Storm flow is frequently mentioned as the predominant source of streamflow in ephemeral reaches (e.g. Boulton et al., 2017; Zimmer and McGlynn, 2017), whereas streamflow in intermittent streams is dominantly driven by the seasonal fluctuations of the near-surface groundwater table (e.g. Uys and O’keeffe, 1997; Sophocleous. 2002; Goodrich et al., 2018; Fritz et al., 2020).

Although extensive research on storm flow generation at the hillslope and reach scale, as well as baseflow contributions to perennial streams has been conducted, there are still few studies on the dynamic controls on the presence of flow in the ephemeral and intermittent reaches (James and Roulet, 2009; Zimmer and McGlynn, 2017). Studies of intermittent streams can be roughly categorised into four scales: (1) continental scale studies based on discharge measurements (Reynolds et al., 2015; Eng et al., 2016; Trancoso et al., 2016; Jaeger et al., 2019) , (2) (nested) catchment scale studies based on wet/dry mapping of the stream network (Godsey and Kirchner, 2014; Sando and Blasch, 2015; Shaw, 2016; Goodrich et al., 2018; Jensen et al. 2017, 2018)~~.~~, (3) single site~~s~~ or ~~the~~ hillslope scale studies based on conventional discharge measurements (Sidle et al., 1995, Ries et al., 2017, Moreno-de-las-Heras et al., 2020)~~.~~, and (4) (multi)-catchment scale studies that are based on continuous measurements of stream~~-~~flow presence and absence with low-cost sensors (i.e. temperature, electric conductivity or flow-sensors and time-lapse cameras) at multiple locations along the stream ~~that are specifically aimed at~~ monitor~~ing~~ the intermittent stream network (Jaeger and Olden 2012; Zimmermann et al. 2014; Zimmer and McGlynn, 2017; Jensen et al. 2019, Kaplan et al., 2020a).The continental scale studies are based on datasets from environmental agencies, which are usually not specifically dedicated to intermittent streams (Reynolds et al., 2015; Eng et al., 2016; Trancoso et al., 2016; Jaeger et al., 2019). These studies of streamflow intermittency commonly use statistical models to predict intermittency ~~at the continental to regional scale and~~ try to incorporate the climatic controls at coarse temporal resolution such as mean or total annual precipitation (Reynolds et al., 2015; Trancoso et al., 2016; Jaeger et al., 2019), ~~annual evapotranspiration (Trancoso et al., 2016),~~ snowpack persistence from e.g. March to July/August or contribution of ~~total~~ annual precipitation ~~in form of snow~~ (Reynolds et al., 2015; Sando and Blasch, 2015; Jaeger et al., 2019), ~~as well as measures like the annual average number of days of measurable precipitation (Reynolds et al., 2015),~~ dryness or seasonality index (Trancoso et al., 2016)~~, or streamflow indicies like zero flow days (Eng et al., 2016)~~. These climatic predictors are used to identify the likelihood of the stream network being spatially intermittent (Reynolds et al., 2015; Trancoso et al., 2016; Jaeger et al., 2019) or to identify long-term changes of streamflow intermittency under a changing climate (Eng et al., 2016). Reynolds et al. (2015) found a generally poor agreement of single climate predictors ~~explaining~~ zero-flow days in the Upper Colorado River Basin and emphasise the importance of interplay between composite of precipitation and temperature to predict zero-flow days. They also highlight the high correlation ~~of~~ the Palmer Draought Severity Index ~~with~~ the degree of stream intermittency. Eng et al. (2016) identif~~y~~ different types of intermittent streams in the USA based on the climatic seasonality that was in some cases overwritten by ~~the geographical layout of the~~ catchments (e.g. local geology). They found intermittency in fall-to-winter primarily caused by precipitation storage in form of snow and ice ~~while~~ streamflow starts again with the onset of snowmelt and sustained only by the stored snow~~, while~~ summer-to-winter intermittency was mainly caused by a periods of low precipitation coinciding with maximum potential evaporation. Precipitation events with amounts similar to those that were not able to initiate flow during the summer-to-winter streamflow intermittency were able to cause flow ~~events~~ later in the year when soil moisture content was higher due to ~~antecedent~~ precipitation events. Non-seasonal intermittent streams mainly appeared in regions with high variability of precipitation and large water deficits caused by evapotranspiration (Eng et al., 2016). Jaeger et al. (2019) present a regional scale model approach for the Pacific Northwest of the USA and found total annual precipitation, minimum annual temperature and the percent forest cover ~~as~~ the most important predictors for flow permanence, while submodels for specific regions highlight the importance of evapotranspiration during the dr~~yer~~ months. The regional variation of ~~intermittency on~~ continental scale in eastern Australia could be best descriped by the dryness index (Budyko, 1974) and photosynthetically active radiation (fPAR), while soil properties had an significant effect on streamflow intermittency at the regional scale (Trancoso et al., 2016).

The (nested) catchment scale studies often rely on a limited number of wet/dry mapping campaigns of the stream network (Godsey and Kirchner, 2014; Sando and Blasch, 2015; Shaw, 2016; Goodrich et al., 2018; Jensen et al. 2017, 2018; Durighetto et al., 2020) These data is used to validated models that predict the dynamics of the wetted channel network~~-~~. Predictors used in these models vary from ~~observed~~ discharge (Godsey and Kirchner, 2014; Jensen et al., 2017) or the recession rate at the catchment outlet (Shaw, 2016) to groundwater recharge data (Goodrich et al., 2018). ~~Godsey and Kirchner (2014) identify total flow length of the drainage network in four California headwater catchments explained by a power-law functions of streamflow with very similar log-log slopes for all catchments.~~ However, drainage network extent does not necessarily correspond to the timing of streamflow recession as shown by Shaw (2016) for a headwater catchment in the state of New York. He noticed the presence of seeps at the channel head of multiple subchannels that ~~were~~ contribut~~ing~~ to flow even when the lower reaches ceased to flow. This suggests ~~that~~ multiple local water tables ~~devlop~~ due to the structure of subsurface ~~features~~ (geological layering, bedrock fractures) and contribute to channel ~~out~~flow at the seeps (Shaw, 2016). The importance of geology on the occurrence of intermittent streamflow ~~is~~ also shown in other climatic settings (Buttle et al., 2012; Jensen et al., 2017; Durighetto et al., 2020). Rainfall timing and intensity were good predictors of stream network dynamics in an Alpine headwater catchment, whereas evapotranspiration had little predictive power (Durighetto et al., 2020). In hillslope scale studies, streamflow is usually measured continuously with conventional streamflow gauges at a single site or in nested sub-catchments and hillslopes (Sidle et al., 1995, Ries et al., 2017, Moreno-de-las-Heras et al., 2020). The streamflow dynamics are typically analysed in combination with hightemporal resolution soil moisture data (Penna et al., 2011; Ries et a., 2017; Zimmer and McGlynn, 2017), local shallow groundwater measurements (Zimmer and McGlynn, 2017; Sidle et al., 1995), ~~and~~subsurface flow observations at a trench (Sidle et al., 1995), as well as with high-resolution ~~local~~ precipitation data. ~~These studies aim~~

~~towards a separation of streamflow into contributions of Hortonian overland flow (HOF), saturation excess overland flow (SOF) or subsurface storm flow (SSF) and groundwater contributions at the event scale.~~ The dependenc~~y~~ of runoff initiation on thresholds of antecedent soil moisture at 10-30cm depth was demonstrated for several climates, topographies and land use characteristics (James and Roulet, 2009; Penna et al., 2011). ~~Penna et al. (2011) found no indication for SOF on the hillslopes and conclude that hillslope contribution to streamflow were primarily SSF. However, the saturated zones from the riparian expanded towards the hillslopes with increasing wetness, which made them hydrologically active.~~ Ries et al. (2017) showed for Mediterranean ephemeral streams that event precipitation sums below 50mm le~~a~~d to streamflow fed by HOF. Above this threshold ~~they found~~ streamflow primarily explained by bedrock permeability, soil water storage and rainfall intensity which control the timing of SOF. The importance of storage variability was also ~~addressed~~ by Zimmer and McGlynn (2017), who found seasonally distinct flow paths depending on the catchment storage state. These seasonal fluctuation of catchment storage were driven by changes in evaportranspiration. During events with low antecendent storage shallow~~,~~ perched~~, transient~~ groundwater at the upper hillslope contributed to streamflow with SOF after a period ~~of~~ HOF at the beginning of the event. ~~In~~ more saturated conditions the deeper groundwater provided baseflow before and after an event and all eventflow was SOF. During this wet state ~~of the system~~ also the stream network extended to its maximum length including zero-order hollows. ~~T~~he understanding of streamflow intermittency ~~controls~~ and drainage network connectivity at the continental, headwater catchment and hillslope-scale have ~~been addressed by the different types of studies described above, but~~ studies of intermittency in meso-scale catchments ~~and for~~ temperate climates still remains scarce.

Some of the recent studies are based on streamflow duration data captured by newly developed sensor technology, such as electric conductivity (EC), temperature- and self-made flow-detection sensorsor time-lapse cameras along the stream network (Jaeger and Olden 2012; Zimmermann et al. 2014; Bhamjee et al., 2016, Zimmer and McGlynn, 2017; Jensen et al. 2019, Kaplan et al., 2020a, Warix et al., 2021). These studies evolved from research ~~which~~ was initially strongly focused on the evaluation of new sensor technologies by comparing timeseries of precipitation inputs to sensor responses (e.g. Bhamjee and Lindsay, 2011; Bhamjee et al., 2016). ~~T~~he temporal dynamics of ~~the~~ longitudinal connectivity and ~~the~~ streamflow continuity in the stream network ~~was analysed~~ based on the temporal high and spatially coarse (2 km spacing) resolution data of streamflow presence and absence ~~(Jaeger and Olden, 2012). Jaeger and Olden (2012)~~ found that position~~ing~~ of streams in the channel network (headwater vs. lower parts) had a higher explanatory power ~~than geology~~ to differentiate between perennial and non-perennial streams. Recent studies have broadened the initial approaches to event-based analyses and the inclusion of additional measures by including the antecedent precipitation index (API) ~~for timespans between 1 and 128 days~~ to ~~capture~~ the antecedent wetness state of the catchment and precipitation measures like rainfall amount, intensity amd duration (Zimmermann et al., 2014; Jensen et al., 2019). These studies also had a lower sensor spacing of 5 and 40 meters. Jensen et al. (2019) ~~investigated the link between peak discharge at the catchment outlet and the maximum wetted fraction of the stream network during precipitation events with principal component analysis. They~~ found that 60% of the variance was explained by 7 to 30 days antecedent precipitation ~~prior to a precipitation event (a proxy for catchment wetness)~~ and 16% by the precipitation. Zimmermann et al. (2014) modeled the connectivity of the drainage network at the event scale using ~~as predictors~~

precipitation characteristics (ie. event duration, maximum precipitation intensity, and total rainfall) ~~as well as the antecedent precipitation index (API)~~. ~~. Connectivity of the drainage network was defined as the total active streamlength devided by the maximum length of the channel network (Zimmermann et al., 2014)~~. They identified total rainfall and maximum precipitation intensity as the major controls and the long-term antecedent wetness (API including 128 days prior to the event) as a minor control of ~~the~~ drainage network connectivity. Warix et al. (2021) found a poor correlation between groundwater residence time~~s~~ and seasonal flow permanence in a semi-arid catchments in southwestern Idaho that are underlain by volcanics, basalt and latite. They observed continuous streamflow at some reaches ~~with~~ seasonally stable groundwater inputs. The seasonal flow permanence in these catchments ~~showed a~~ high correlat~~ion~~ with topographic metrics (contributing area, slope, topographic wetness index), but groundwater and topography only explained half of the observed variability in streamflow intermittency.

With this study we aim to close the research gap of temporally variable drivers of intermittent streams in temperate climates and diverse geologies. We benefit from a large dataset of observations on the presence or absence of flow (Kaplan et al., 2019), high-resolution precipitation (Neuper and Ehret, 2019), soil moisture and temperature data (Zehe et al., 2014; Demand et al., 2019; Mälicke et al., 2020) collected in the meso-scale Attert catchment. These data was collected and processed in the framework of the research project “Catchments As Organized Systems” (German Research Foundation (DFG), Research Unit FOR 1598). In a previous study, three distinct main geologies were identified as major spatial controls of streamflow intermittency (Kaplan et al., 2020a). We now take this a step further and evaluate the relationship between geology and the temporal ~~dynamic~~ predictors of streamflow intermittency. Following the approaches of Zimmermann et al. (2014) and Jensen et al. (2019), we present an event-based analysis of precipitation and streamflow responses. Similar to their approaches, measures of antecedent precipitation and precipitation event characteristics are considered~~. Howeverm~~ we ~~furthermore~~ also include soil moisture and soil temperature in a random forest modelling approach. We aim to answer the following questions: (1) which types of rainfall events trigger a streamflow response in intermittent streams and which do not~~,~~ (2) what are the main dynamic controls~~/~~predictors of streamflow ~~responses~~ in intermittent streams, and (3) are the controls~~/predictors~~ of intermittent streamflow dependent on the geological setting ~~of the catchment~~?

2. Research area

The Attert catchment is located in the mid-west of Luxembourg, with a minor area located in Belgium, and has a catchment area of 247 km² at the outlet at Useldange (Hellebrand et al., 2008). Devonian slate is the dominant bedrock in the northern part of the catchment in the Luxembourg Ardennes, the central part consists of Keuper marls, and the southern part of the Jurassic Luxembourg sandstone formation (Fig. 1, Martínez-Carreras et al., 2012). The elevation is highest in the Ardennes and Luxembourg sandstone formation at 549 m a.s.l. and 440 m a.s.l., respectively, while the ~~catchment~~ outlet in Useldange is located at 245 m a.s.l. (Martínez-Carreras et al., 2012; Pfister et al., 2018). The Luxembourg Ardennes are characterised by steep inclined valleys with forested hillslopes (ca. 15-25°) and plateaus with agricultural land use. The central part of the catchment consists of gentle hills (slope ca. 3°) that are mainly used for agriculture, grassland, and forest. The sandstone areas are characterised by steep hillslopes that are dominantly forested and in the lower part used as grassland and for agriculture (Kaplan et al., 2020a). Soils in the Attert catchment are linked to lithology, land cover and land use (Cammeraat et al., 2018). Soils in the slate geology are dominated by stony silty soils, while the soils in Keuper marls have silty clayey texture and the Luxembourg sandstone region is largely covered by sandy and silty soils (Müller et al., 2016). On slate the soil depth to the weathered C horizon is usually ~~below~~ 50cm, while the soils on the marls are more heterogenious with a clay rich layer (> 50 % clay) starting between 20 and 50cm depth (Demand et al., 2019). The soil depth to the unweathered bedrock can reach more than 2 m in ~~S~~andstone and Bt horizons are often deeper than 1m (Sprenger et al., 2015).

The climate is classified as pluvial oceanic (Wrede et al., 2014). Annual precipitation ~~amounts~~ vary from 1000 mm in the ~~Ardennes in~~ the north-west to roughly 800 mm ~~in the Luxembourg sandstone~~ in the south-east (Pfister et al., 2017). The mean monthly precipitation ranges from 70 mm in August and September, to 100 mm in December until February (Wrede et al., 2014). Evapotranspiration ~~fluctuates significantly and~~ is higher during summer (82 mm~~) observed~~ in July when the average temperature is 17°C and lowest in winter (13 mm~~)~~ in December when the average temperature is 0°C (Wrede et al., 2014). Theseasonal fluctuations in precipitation and evapotranspiration influence the runoff regime, resulting in high flows during the winter season, while low flows occur in the summer ~~months~~ (Wrede et al., 2014). Spatial differences in the seasonal variation in streamflow depend on the bedrock permeability which controls the storage mixing and release of water in the Attert catchment (Pfister et al., 2017). The sandstone geology in the Attert catchment provides the largest total and active storage (defined as the maximum interannual variability in catchment storage) compared to marl and slate (Pfister et al., 2017). Thus, the sandstone geology has the lowest proportion of active storage compared to total storage (15-26%), while this ~~relationship shows~~ higher ~~values~~ in the slate (69-82%) and marls (69%). ~~Closeby marly~~ catchments ~~showed a~~ up to 100% of total storage ~~was active storage on the Keuper marls~~ (Pfister et al., 2017). Kaplan et al. (2020) demonstrated the importance of bedrock permeability and soil hydraulic conductivity for streamflow intermittency in the Attert catchment. They also highlighted the potential of streamflow alteration through either artificial surface and subsurface drainage, dams and trenches in the agricultural areas as reported by Schaich et al. (2011) and ~~the return~~ flows from wastewater treatment plants on the plateaus of the Ardennes. The drainage density of the perennial streamnetwork derived from the topographic map of the region (Le Gouvernment du Grand-Duché de Luxembourg, 2009) is 1.4 km/km² and 0.6 for intermittent streams. The drainage density varies among the three geologies with 0.8 km/km² ~~for perennial streams~~ and 0.2 km/km² for intermittent on sandstone, 0.7 km/km² ~~for perennial streams~~ and 0.3 km/km² for intermittent streams on marls and 1.0 km/km² ~~for perennial streams~~ and 1.0 km/km² for intermittent streams on slate.

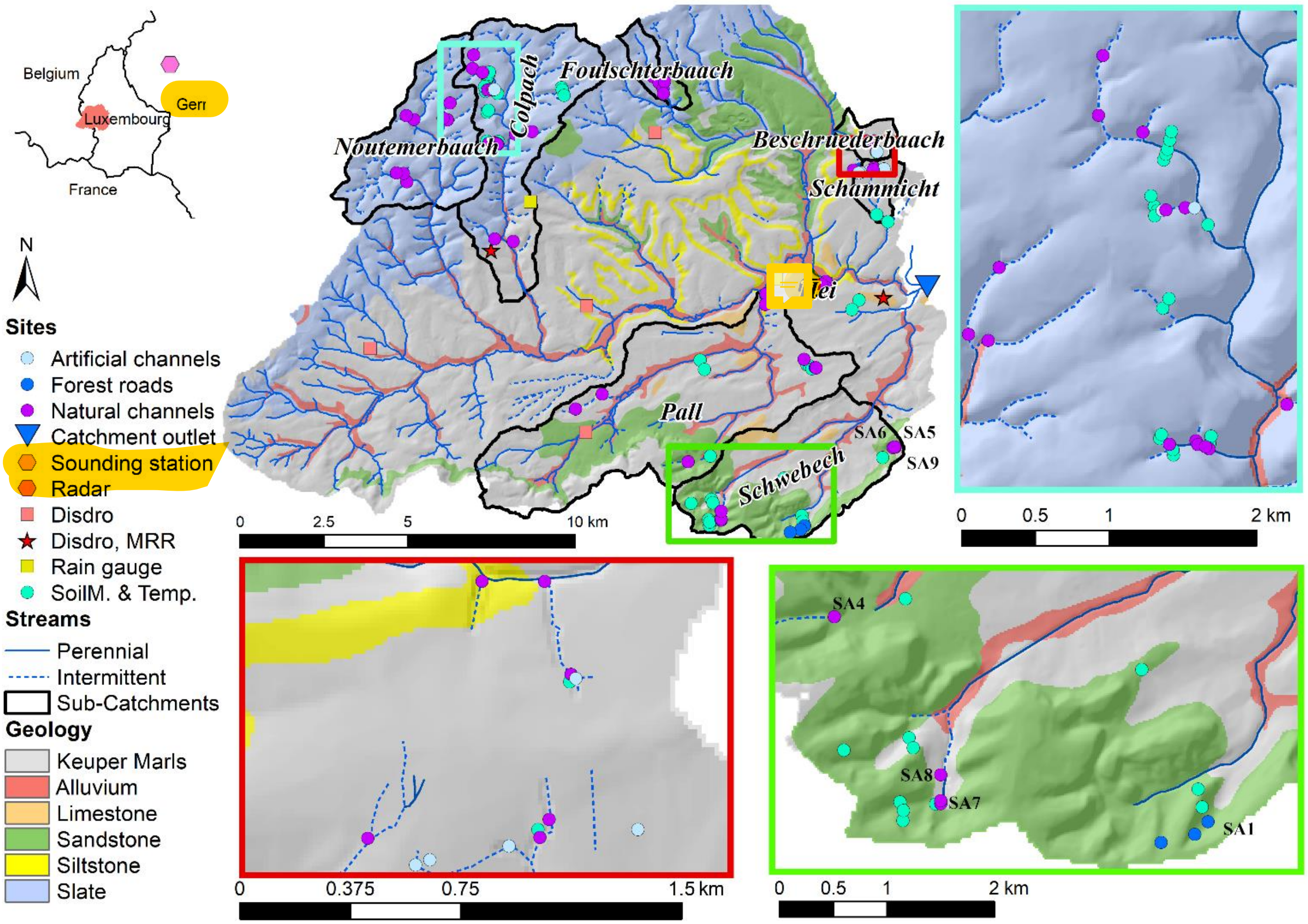

Figure 1: Geology and stream network of the Attert catchment and the locations of streamflow monitoring at artificial channels, forest roads and natural channels, as well as the ~~sites of~~ soil moisture and temperature measurements. Sites with intermittent flow were used for analyses in this study, while the sites with perennial flow were used as pour point sites to delineate the catchment boundaries for the eight sub-catchments “Noumtemerbaach”, “Colpach”, “Foulschterbaach”, “Beschruederbaach”, “Schammicht”, “Hei”, “Pall” and “Schwebech” (~~catchment boundaries derived from~~ a 15m DEM). The map sections show the more intensively instrumented areas in each geology: slate (blue frame), marls (red frame) and sandstone (green frame). Selected sites in the sandstone geology are labled with the~~ir~~ ID (e.g. SA1) ~~as~~ used in the discussion. The geological map from 1947 was provided by the Geological Service of Luxembourg (adapted from Kaplan et al., 2019), the stream network was derived from a topographic map (Le Gouvernment du Grand-Duché de Luxembourg, 2009).

3. Methods

3.1 Data acquisition

We used the intermittency dataset described in Kaplan et al. (2019), which is a binary data set of streamflow presence or absence for 182 ~~gauging~~ sites in the Attert catchment. The gauging sites ~~in this dataset~~ were predominantly located at natural streams, but also comprise smaller channels at ditches and ~~at~~ three sites in ~~the~~ sandstone erosion channels on forest roads. Gauging sites at artificial channels were mainly located in the less natural landscape on the marl geology (see Fig. 1). Thus, the definition of "an intermittent stream" in this study is a natural or artificial channel with occasional surface runoff. The data were collected using various sensors, including time-lapse imagery (Dörr Snapshot Mini 5.0), electric conductivity sensors (Onset HOBO Pendant waterproof temperature and light data logger), and conventional gauges (METER/Decagon CTD pressure transducers in stilling wells at weirs). Time lapse imagery was predominantly installed at sites that were expected to have intermittent streamflow, EC-sensors at locations with expected perennial flow and conventional gauges at catchment outlets ~~as well as~~ close to the soil moisture measurement sites (Kaplan et al., 2019). Therefore, a subset of gauges with intermittent streamflow was selected comprising the sites which were monitored by time-lapse camera (C) and conventional gauges (CG). Intermittent streamflow is here defined for the observed streamflow at gauging sites showing at least a period of one hour with no flow. The subset was split into further subsets according to the dominant geology (marl, sandstone, slate) of the upslope contributing area. For the different geological regions these subsets comprised 22 gauging sites in slate, 23 in marl and nine in sandstone (See Figure 1 and Figure 3). The contributing area derived from GIS-analysis using a DEM (15m resolution) of all intermittend streamflow gauging sites (Kaplan et al., 2020a) is shown in figure S1 in the supplement. The streamflow data was aggregated from the original temporal resolution ~~of 15 min~~ to one-hour intervals by calculating the mean of the binary values and rounding (threshold: 0.5) the resulting value to one digit, i.e. back to binary values (0/1).

Soil moisture and soil temperature were measured at 45 sites (hereafter "soilmoisture sites") across the catchment with each site ~~having~~ three soil profiles ~~providing a~~ total ~~of~~ 135 soil profiles (Figure 1). In each profile, combined soil moisture and temperature sensors were installed at ~~depths of~~ 10, 30 and 50cm below the surface and recorded data have a temporal resolution of five minutes. The soil moisture sites were located in each of the three main geologies in the catchment in either forest or grassland (see Table 1). Combined, these two land cover classes represent the predominant land cover in the catchment (Kaplan et al. 2019). In the marls and slate regions, agricultural land use has a substantial share of 41% and 42%. However, in agricultural land use permanent sensor installations are not feasible and the natural stream network is heavily altered by artificial drainage systems. The soil moisture sites were chosen for the best possible representation of the combined land use and geology at a variety of slope gradients, expositions (North, South) and position on the slope (top, mid, valley) and thus, were arranged along different hillslope transects, covering different positions on the hillslope, different slopes and aspects. The soil moisture sites were part of a sensor cluster network (e.g. climate variables, sap flow, local groundwater) that was initially set up to experimentally test the concept of elementary functional units as proposed by Zehe et al. (2014). Eleven sites were located in the marl region, 22 sites were in the slate region and 12 sites in the Sandstone ~~with~~ a total of 33, 66 and 36 soil moisture measurement profiles per geology, respectively (Table 1). Although ~~some~~ land cover classes ~~are not covered by the sites~~, the assumption was made that the sites represent the general soil moisture dynamics in the three geologies. The first measurements started in March 2012 to October 2013 and ended in February 2018. In this study, a subset of the data for the period from 01.04.2016 until 17.07.2017 was used, because it has the largest overlap between the other data sources used in this study. Initially we installed 5TE capacitance sensors (Decagon Devices/METER Environment, USA), but due to sensor malfunction, 43 sensors were replaced with SMT100 (TRUEBNER GmbH, Neustadt, Germany) and nine sensors with GS3 sensors (Decagon Devices/METER Environment, USA) in 2016. The data was visually checked and offsets between soil moisture measurements after sensor replacement were detected in four timeseries. Additionally, seven timeseries with strong sensor noise and/or extensive periods of constant soil moisture were ~~identified and~~ removed from the dataset. The soil moisture values were normalised to the minimum and maximum of the time series for each sensor to avoid possible bias among sensors. Soil moisture dynamics at each geology are represented by the mean of the normalised time series for all sites located in the corresponding geology. The soil moisture data was aggregated to hourly means. The averaged soil moisture was assigned to the streamflow gauging sites based on the main geology at the site.

Neuper and Ehret (2019) estimated precipitation from weather radar data combined with data from six disdrometers, two micro rain radars, regular rain gauges, and weather radar reflectivity (locations see Fig. 1) using an information theory approach. This precipitation dataset was used in this study due to its high temporal (1 hour) and spatial (100 m) resolution. The precipitation data from this gridded dataset was used at the locations of the intermittent stream gauging sites. The precipitation data at the gauging sites was thereafter used to calculate precipitation averages for the eight sub-catchments (Fig. 1) ~~for a catchment scale analysis of precipitation events. Averages of the precipitation time series were calculated as the average of precipitation at all stream gauging sites within the catchment~~ without further spatial interpolation.

Table 1: Number of soil moisture and temperature measurement sites for each geology and land use. Each site has three soil profiles with soil moisture and temperature sensors ~~in~~ 10, 30 and 50 cm depth.

	~~Land use~~	
Geology	Forest	Grassland
Slate	15	7
Marls	5	6
Sandstone	9	3

3.2 Definition of precipitation events and streamflow response

Event analysis was carried out for the time period 01.04.2016 to 17.07.2017, the period ~~which covers~~ the maximum overlap of the available data. In accordance with Wiekenkamp et al. (2016) and Demand et al. (2019), a precipitation event was defined as having a minimum precipitation sum of 1 mm. The required time period of no precipitation to separate two successive events was defined as three hours (3h), after testing a set of four different values (3, 6, 12 and 24 hours without rain, Penna et al. 2011; Penna et al. 2015; Demand et al., 2019). The maximum time between the start of a precipitation event and the start of the streamflow response was limited to 48 hours after testing, both the 24 and 48 hours as thresholds (Figure 2). In the case of multiple precipitation events within 48 hours before the streamflow response, the latest precipitation event before the streamflow response was chosen as the initialising precipitation event. The following characteristics were calculated for each event: Cumulative Antecedent Precipitation (CAP) ~~with~~in 24h before the ~~precipitation~~ event and the seven and 14 day antecedent precipitation index (API):

$$API = \sum_{t=-1}^{-i} P_t k^{-t} \tag{1}$$

with P_t as the precipitation during time step t, i the number of antecedent time steps (7 or 14 days) and k as a decay constant (Kohler and Linsley, 1951). Values for the decay constant usually range between 0.80 and 0.98 (Heggen, 2001). A value of 0.85 was ~~used in~~ this study~~. This value was chosen~~ to minimise the correlation between the API and CAP ~~measure.~~ Additional event characteristic~~ measure~~s included the maximum precipitation intensity (P_{max}), mean precipitation intensity (P_{mean}), total sum of precipitation (P_{sum}), duration of the precipitation event (P_D), and the normalised soil moisture (averaged per geology)at 10 cm (θ_{10}, Fig. S2), 30 cm (θ_{30}) and 50 cm (θ_{50}) depth at the first and last time step of the precipitation event, as well as the minimum, mean, and maximum soil moisture. ~~Soil moisture data was assigned to gauging sites based on the predominant geology in the catchments of the gauging sites.~~ We also used the minima~~l~~ soil temperature during the precipitation event (T_{min}, Fig. S3) as a proxy of seasonal changes in temperature and the corresponding fluctuations in evapotranspiration (Wrede et al., 2014) as well as a potential identifier of freezing conditions. The soil temperature was used due to its lower daily variability and lower dependenc~~y~~ on the microclimate at the site ~~which allows for~~ a better representation of ~~an~~ average temperature for each geology.

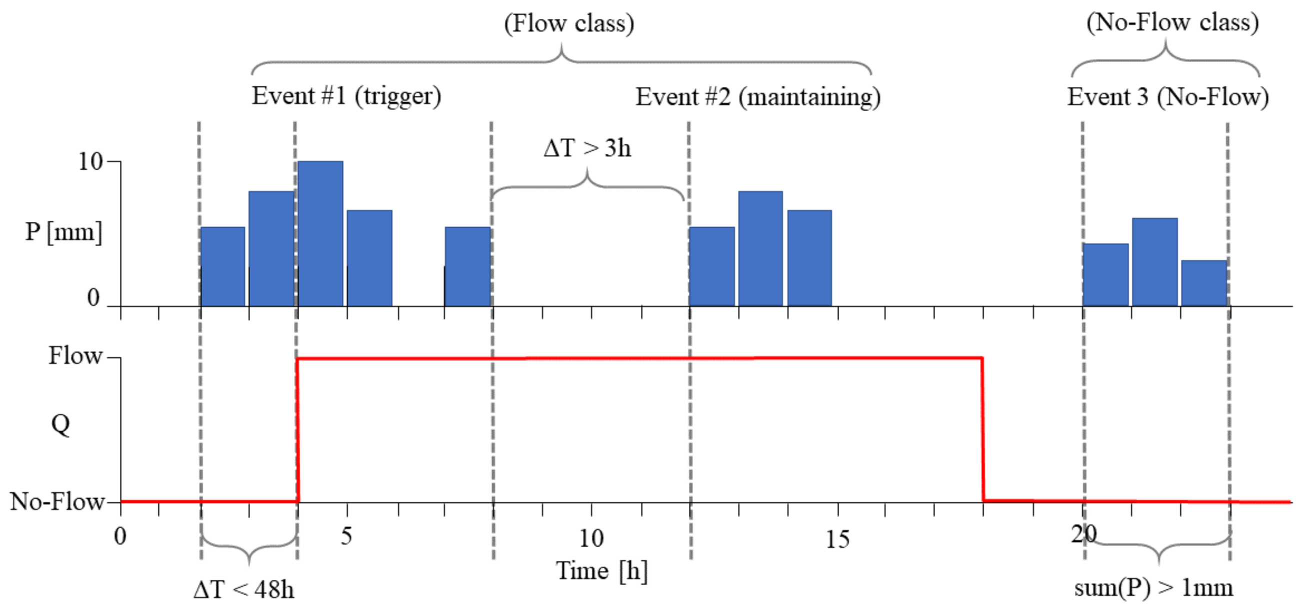

Figure 2: Precipitation events are defined by a minimum precipitation sum of 1mm separated by at least three hours on no precipitation (ΔT > 3h). Flow events are assigned to the last precipitation event within 48 hours before ~~the~~ flow initialisation (ΔT < 48h). Precipitation events are classified as either triggering or maintaining ~~events for the corresponding streamflow events~~ and ~~summarised in the~~ "flow class" or ~~classified as~~ "no-flow" ~~in cases without~~ streamflow response within 48 hours after the precipitation event.

Events were classified according to the presence or absence of flow at the stream gauges. Precipitation events which triggered the initialisation of a streamflow response within 48h after the event – according to the definition above – were classified as "flow initialising". Precipitation events ~~which have no~~ flow responses are classified as "no-flow". Those precipitation events that are classified neither as flow initialising nor as no-flow response and happen ~~during flow events~~, are classified as "flow maintaining". For the purpose of modelling streamflow responses, the two classes flow-initialising and flow-maintaining were merged into one response class named "flow" (Figure 2), because we assume from the event data that preconditions for flow initiation and maintenance are ~~highly~~ similar. The event definition and streamflow classification were carried out ~~both~~ for rainfall measured locally in the grid cell at the stream flow monitoring sites as well as catchment averaged rainfall for each of the eight sub-catchments "Pall", "Beschruederbaach", "Hei", "Schammicht" (marl geology), "Schwebich" (sandstone geology), "Noutemerbaach", "Colpach" and "Foulschterbaach" (slate geology, Figure 1, Table 2~~: Number of gauging sites per sub-catchment, precipitation sums and the percentage of catchment geology. Missing values to 100% for the geology represent minor geologies and alluvium.~~). The precipitation events for each sub-catchment are based on the same spatially averaged catchment precipitation data and are thus identical for all sites within a sub-catchment. The spatial aggregation of precipitation data is possible due to the very high correlation between the precipitation at the single sites in the sub-catchments (fig. S4). Thus, for each site responses to the precipitation event can be "flow", "no-flow" or "NA" in cases of larger data gaps in the flow data.

Table 2: Number of gauging sites per sub-catchment, precipitation sums and the percentage of catchment geology. ~~Missing values~~ to 100% ~~for the geology represent minor~~ geologies and alluvium.

	Number of sites per catchment & geology			Catchment geology [%]			
Catchment	Slate	Marls	Sandstone	Slate	Marls	Sandstone	P_{sum} [mm]
Foulschterbaach	5	0	0	86	0	14	687
Colpach	14	1	0	81	15	1	634
Noutemerbaach	3	0	0	98	0	0	637
Pall	0	7	1	0	64	22	592
Beschruederbaach	0	4	0	0	73	16	593
Hei	0	2	0	0	93	0	645
Schammicht	0	8	0	0	100	0	603
Schwebich	0	0	9	0	47	41	573

3.3 Random forest model for intermittency

In general, a random forest (RF) model contains an ensemble of regression trees. Predictions of a RF model are based on the averaged predictions of all trees in the forest (Breiman, 2001). A RF model is created by bootstrapping several random samples from the original data and fitting a single classification tree to a bootstrapped sample (Out Of Bag samples (OBB)). Validation of the OBB classification is performed with the data ~~remaining outside of~~ the bootstrap sample ~~(OBB)~~. This data is used for independent predictions for each OBB based tree. From these predictions the OBB error rate is calculated over all trees to provide a measure of the predictive performance of the model (Breiman, 2001).

Multiple RF models were used to model the classes of streamflow responses (flow or no-flow) as a function of the predictor variables (Table 3). Table 3 includes the selected predictor variables. Only the maximum soil moisture at 10cm and 50cm depth (θ_{10} and θ_{50}) were selected due to high correlations (Kendall's $\tau > 0.8$) among the other soil moisture predictors~~: initial, end, minimum and mean soil moisture during a precipitation event in the different depths~~ (see Fig. S5). The correlation ~~among the predictors in table 3~~ was low among most of the predictors only the soil moisture measures in the two depths and API ~~with~~ the two periods ~~had~~ higher ~~correlations~~ for most sites (see Fig. S6 – S8). For each site an individual random forest model with the dataset containing the classification of streamflow responses and the corresponding predictor variables was set up. This is necessary as the number of complete precipitation events with streamflow responses varies considerably among the sites due to gaps in the streamflow observations and the variance of precipitation patterns and timing in the catchment (40 to 119 precipitation events, see Fig. 3 and Tab. S1, S2, S3) ~~and hence a common dataset is not feasible. However,~~ despite the varying number of precipitation events, the importance of temporal predictors on the streamflow responses to the precipitation events can still be analysed for each site.

The dataset was split into a training dataset (70% of the data) for model fitting and a test dataset (30% of the data) for model validation. Several training datasets ~~showed~~ highly unequal number~~s~~ of flow or no-flow responses, which would lead to an overfitting of the model to the class with a higher number of responses. Thus, ~~the~~ two methods of data resampling from the R-package ROSE (Random Over-Sampling Examples, Lunardon et al., 2014) were used to avoid ~~the~~ overrepresentation of one class. The oversampling function ~~from the ROSE package~~ performs simple oversampling with replacement from the minority class until the specified sample size N is reached. With the option *both* of the ROSE package the minority class is oversampled with replacement and the majority class is undersampled without replacement until the sample size N is reached. The resampling is carried out with the probability for the minority class given by the value p (in this study 0.5; Lunardon et al., 2014). Oversampling was set up to generate a dataset holding twice the number of observations of the overrepresented class, whereas the over-/under-sampling aims for the 1.5-fold number of all events contained in the original dataset. Thus, three different datasets were ~~tested~~ as training data: a) the original training dataset, b) a resampled training dataset after using the oversampling function of ROSE and c) a resampled training dataset using the over-/under-sampling (called “both”) function of ROSE. In a first run, the three different datasets for each site were used to fit three random forest models which were validated with the corresponding test dataset. The random forest models were run with the R-package “randomForest” (Liaw and Wiener 2002) with a randomly chosen seed set to 123 to ensure reproducibility of the statistical model, the number of trees was set to 2500 after reaching stable OBB error rates around this threshold and three predictor variables ~~tried~~ at each split ~~as the default value~~. The confusionMatrix function from the R-package “caret” (Kuhn et al., 2015) was used for validation. The confusion matrix compares the modelled with the observed values and allows e.g. to quantify the percentage of correct and false classified classes and overall accuracy of model results as total correct classifications. Only models with an averaged sensitivity (correct flow predictions / total flow observations) and specificity (correct no-flow predictions / total no-flow observations) > 0.5 and a sum of both measures higher than one were considered for further analysis. The dataset with the highest averaged sensitivity/specificity was chosen for each site for further analysis. In cases where multiple datasets for a site had the same values of sensitivity/ specificity, the original data was chosen over the resampled datasets. The model accuracy (total correctly classified events / total number of modelled events) was used as an additional indicator for the assessment of model quality but was not used during the evaluation process.

With one dataset selected for each site, one model was run for each site and the mean decrease Gini (MDG) was obtained only for those models based on the selected datasets by using the “importance” function from the R-package “randomForest”. The MDG is calculated for each predictor variable X in the random forest model. For each decision tree in the model, the summed-up decrease of the node impurity measure (the Gini index) is weighted by the proportion of data points reaching the nodes that are split by the specific predictor variable. These decreases in Gini index for single trees are averaged over all trees in the forest to obtain the mean decrease Gini (Louppe et al., 2013). A higher mean decrease in Gini indicates higher variable importance. The MDG is recognised as a robust measure to rank the importance of the predictor variables of the random forest models (Calle and Urrea, 2010).

Table 3: Predictor variables used in the random forest model selection.

Predictor	Abbreviation
Mean event precipitation intensity [mm/h]	P_{mean}
Event precipitation sum [mm]	P_{sum}
Maximum Event precipitation intensity [mm/h]	P_{max}
Cumulative antecedent precipitation (24h) [mm]	CAP
Antecedent precipitation index (7 days) [mm]	API_7
Antecedent precipitation index (14 days) [mm]	API_14
Maximum normalized soil moisture at 10 cm depth during the event [-]	θ_{10}
Maximum normalized soil moisture at 50 cm depth during the event [-]	θ_{50}
Duration of the precipitation event [h]	P_D
Minimum soil temperature during an event [°C]	T_{min}

4. Results

4.1 Event analysis

4.1.1 Event analysis based on local rainfall characteristics

~~For the 22 sites in the slate geology,~~ between 64 and 119 events were identified (Figure 3, Tab. S1). The differences ~~in detected precipitation events~~ were caused by the natural spatial variability of precipitation but also by data gaps in the streamflow response dataset. For 17 sites, the precipitation events led predominantly to flow responses, while no-flow responses were only dominant for five sites (Figure 3). The share of no-flow responses at the sites ranged from 3% to 89%. For one site – although having intermittent flow – no precipitation event ~~was observed which had~~ a no-flow response~~r~~. For the 23 sites located in the marl geology, between 51 and 114 events were identified. Twelve of these had more flow responses to precipitation than no-flow responses, while eleven sites ~~had~~ more no-flow responses (Tab. S2, Figure 3). The percentage of no-flow responses ranged between 14% and 93%, but for one site there were not any detected no-flow response. The total number of precipitation events for the nine sites in the sandstone geology varied between 40 and 110 (Tab. S3, Figure 3). There was a nearly equal split of sites with predominance in flow (5 sites) and no-flow (4 sites) responses. The proportion of no-flow responses to the total number of precipitation events ranged from 3 to 82 %. Generally, the number of flow responses to precipitation events were lower in the marl geology (Figure 3).

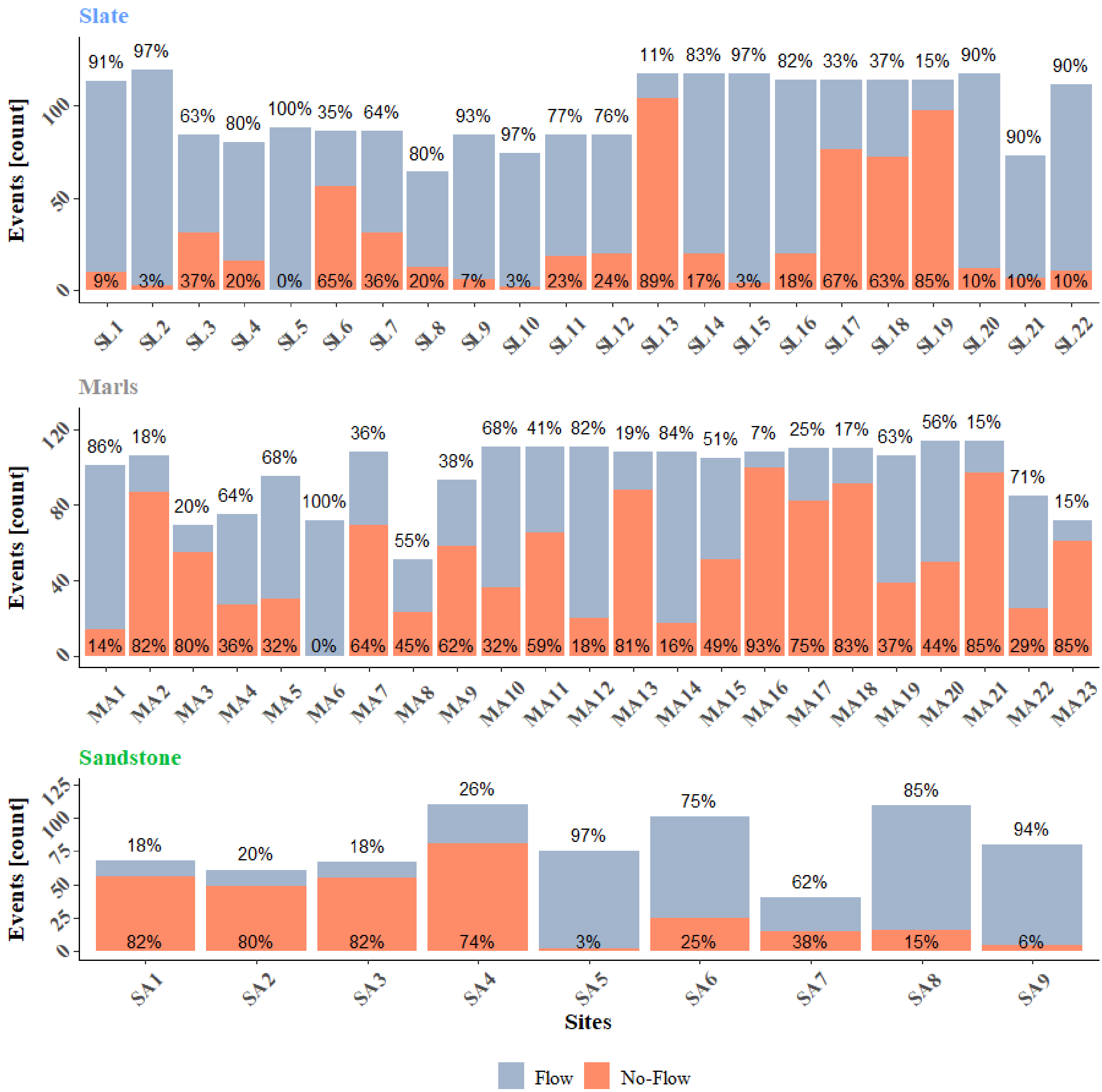

Figure 3: Number of precipitation events resulting in either a flow or no-flow response for the sites underlain by different geology: slate, marls, and sandstone. The average percentage of flow ~~to no-flow~~ responses per geology are 70,8 % ~~to 29,2%~~ in slate, 47,4% ~~to 52,6%~~ in marls, and 57,2 % ~~to 42,8 %~~ in sandstone.

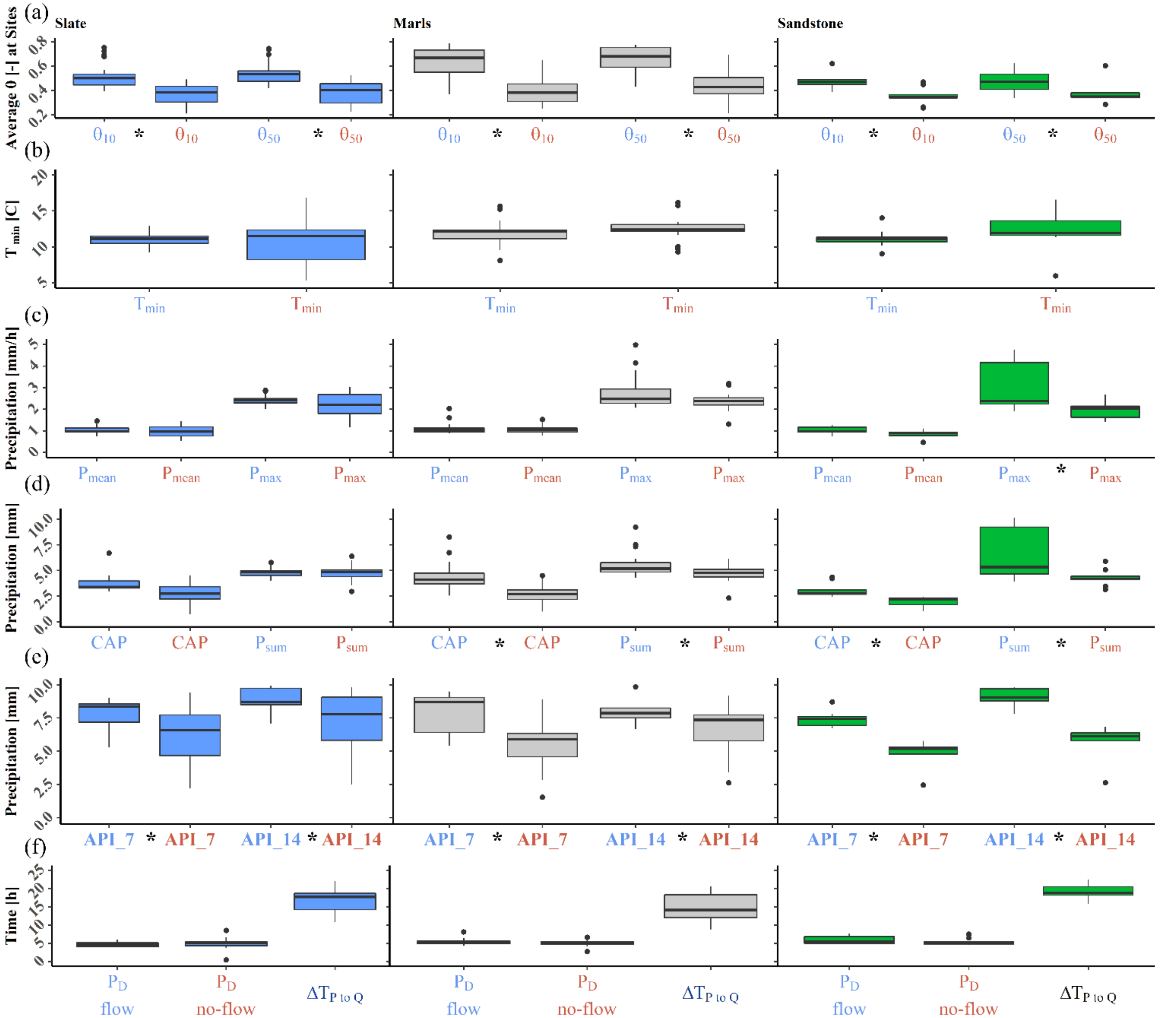

Figure 4: **Flow (blue x-axis labels) and no-flow (red labels) responses in the three geologies (slate, marls, sandstone) ~~are shown with their~~ (a) averaged maximum soil moisture ~~in~~ 10 cm and 50 cm depth during precipitation events, (b) averaged minimum soil temperature ~~in~~ 10 cm depth durign the precipitation event, (c) precipitation intensity ~~P_{mean} and P_{max}~~, (d) the cumulative antecedent precipitation (CAP) and the cumulative event precipitation (P_{sum}), (e) the 7 and 14-day antecedent precipitation index (API_7 / API_14) and (f) the duration of precipitation events (P_D) as well as the time between initial precipitation and flow initiation ($\Delta T_{P\ to\ Q}$). One outlier ~~of~~ P_{mean} (6.5 mm/h) in slate is not shown to enhance the readability ~~of the plot by reducing the scale maximum~~. The boxes show the 25th and 75th percentile, outliers ~~are marked if they reach values higher than~~ 1.5 ~~of~~ the interquantile range from the box boundaries ~~of quantiles Q1 and Q3~~. Significant differences (two sided t-test) between flow and no-flow responses for predictor values within ~~a~~ geology are marked with a star symbol.**

The differences of the averaged values of the predictors at each site between flow and no-flow responses were tested with a two sided t-test seperatly for each geology. The results of the t-test show significantly ($p < 0.05$) higher average soil moisture at sites for flow responses compared to the no-flow responses (Figure 4a). The largest differences ~~of~~ soil moisture i~~n both depths~~ between flow and no-flow responses were observed ~~in~~ the marl geology, with a mean θ_{10} of 0.63 and θ_{50} of 0.66 during flow responses compared to 0.38 (θ_{10}) and 0.44 (θ_{50}) during no-flow responses (Figure 4). The difference in soil moisture were smallest for the sandstone with θ_{10} of 0.48 and θ_{50} of 0.47 during flow responses and 0.35 and 0.36 respectively during no-flow responses. Soil moisture ~~of sites in the slate~~ was slightly higher than in the sandstone ~~with~~ θ_{10} of 0.52 and θ_{50} of 0.55 ~~during flow responses~~ and 0.37 in both depths ~~($\theta_{10/50}$)~~ during no-flow responses. In contrast to soil moisture, the averages for minimum soil temperature did not differ significantly between flow and no-flow responses (Figure 4). Also, the precipitation measures P_{mean}, P_{sum} and P_{max} were very similar for flow and no-flow responses at sites ~~within the~~ slate and marl geology (Figure 4c). However, the t-test showed significantly higher values for P_{sum} and P_{max} for flow responses (P_{sum} = 6.4 mm, P_{max} = 3 mm/h) compared to no-flow responses (P_{sum} = 4.3 mm, P_{max} = 2 mm/h) for the sandstone as well as a significantly higher P_{sum} during flow responses (P_{sum} = 5.5 mm) than no-flow responses (P_{sum} = 4.6 mm) for the marl. While the API_7 and API_14 varied significantly between flow and no-flow responses across all geologies, the 24 hour cumulative antecedent precipitation was significantly higher for flow responses in marl (CAP_{flow} = 4.7 mm, $CAP_{no\text{-}flow\,=}$ 2.7 mm) and sandstone (CAP_{flow} = 3.1 mm, $CAP_{no\text{-}flow\,=}$ 1.9 mm) (Figure 4d, e) compared to no-flow responses, but the differences in the slate were not significant. The duration of a precipitation event was not significantly different between flow or no-flow responses ~~as they were very similar despite a~~ slightly longer ~~precipitation duration~~ for flow responses in the sandstone (Figure 4f). However, there are noteworthy differences in the lag between initiation of the precipitation events and the begin of the streamflow response (Figure 4f). The sites in marl have the shortest~~, slate sites intermediate~~ and sandstone sites the longest response times.

4.1.2 Event analysis based on sub-catchment averaged rainfall characteristics

The response data for the catchments “Pall”, “Beschruederbaach”, “Hei”, “Schammicht” (marls catchments ~~depicted in grey~~), “Schwebich” (sandstone catchment ~~depicted in green~~), “Noutemerbaach”, “Colpach” and “Foulschterbaach” (slate catchments ~~depicted in blue~~) is shown in Figure 5. The mapped data reveals large differences in flow responses, even between catchments that are located close to each other. The two small sub-catchments within the Hei catchment are prominent examples of two ~~catchments with~~ gauging sites that were less than 500m apart but ~~had~~ very different shares of flow (eastern site: 56% ; western site: 15%) and no-flow responses (~~0.~~44%; ~~0,~~85%; Figure 5).

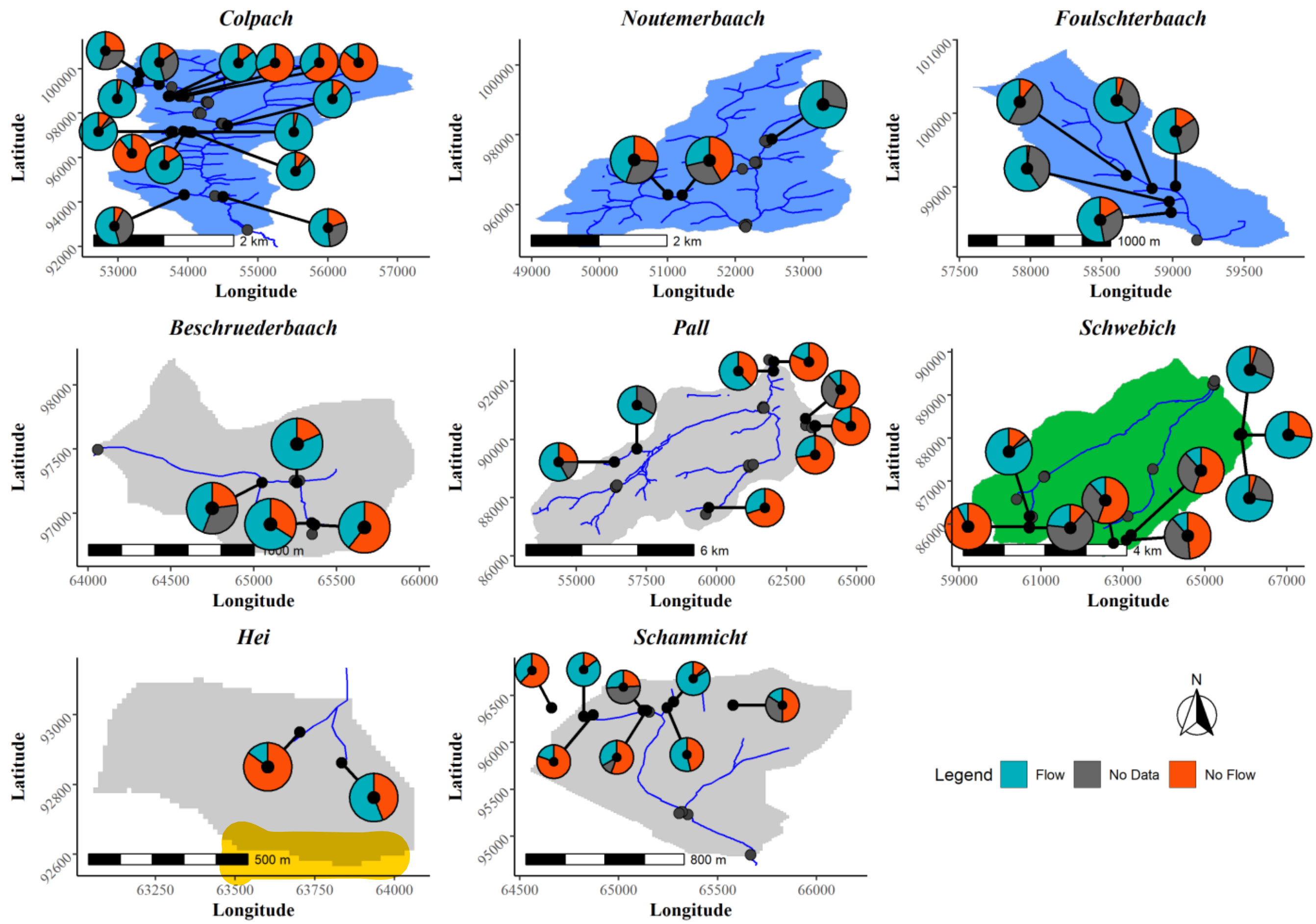

Figure 5: Maps of the sites and their corresponding proportion of flow responses. The prevalent geology at the majority of the sites in each catchment is indicated by the colour of the catchment: blue = slate, grey = marls and green = sandstone. The geology at the site does not always reflect the dominant geology of the entire catchment.

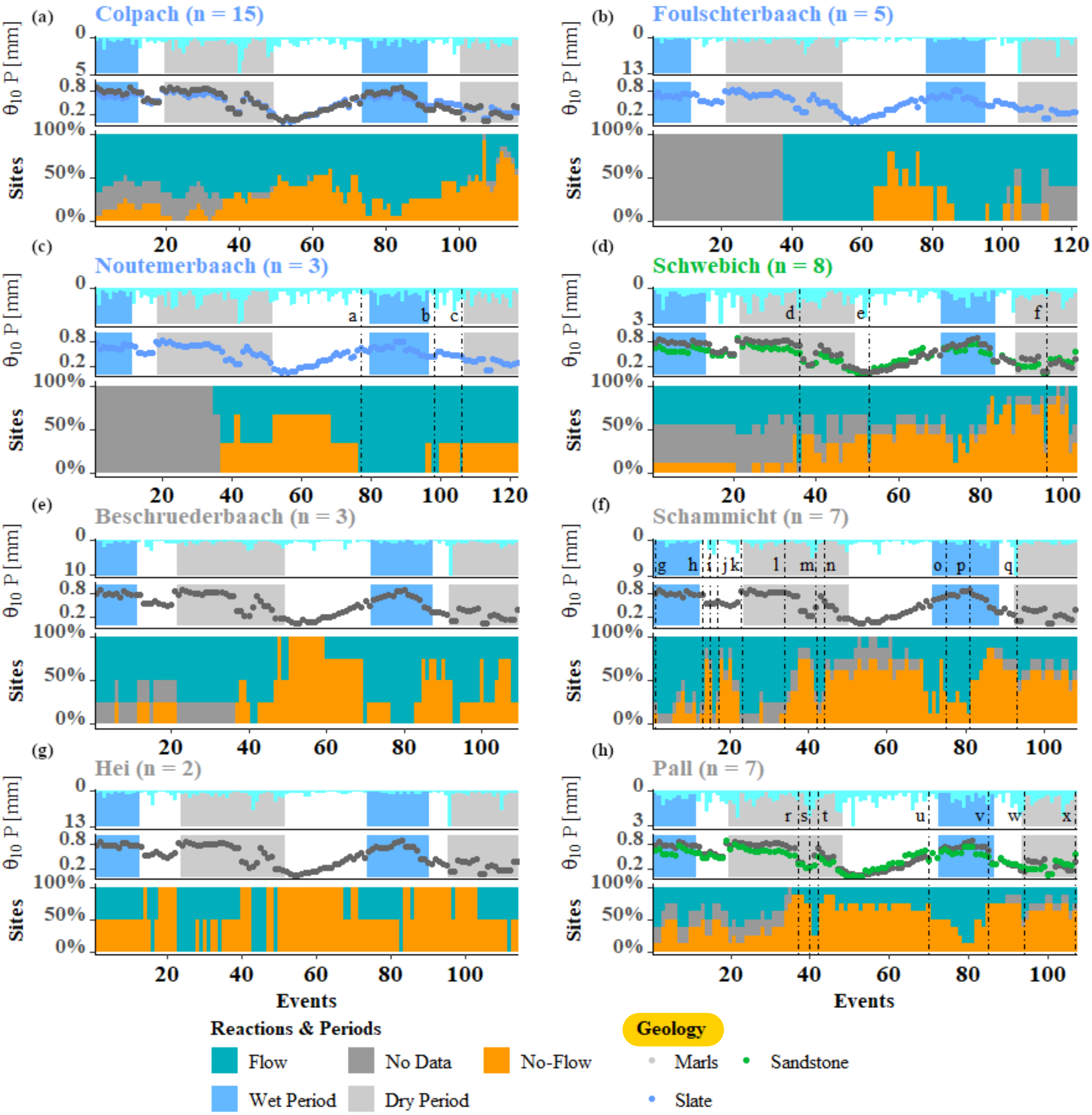

Figure 6: ~~Event dynamics for each catchment ordered by their temporal succession. Each sub-plot shows the~~ mean event precipitation (top), soil moisture in 10 cm depth (mid) and the ~~proportional share~~ of sites in the catchment with ~~the response categories~~ "flow", ~~"no data"~~ or "no-flow". For sub-catchments with sites in two different geologies, the soil moisture ~~dynamics~~ for each of the geologies ~~are shown. In addition,~~ the events in the months February, March and April are highlighted with a blue background representing a period with a high number of sites in the Attert catchment with flow, whereas the months June, July and August highlighted with a gray background indicate a dry period. Specific events are highlighted with dashed lines and labled with letters for reference. The colour of the header of the sub-plot represents the dominant geology (blue = slate, gray = marls, green = sandstone). The header also includes the number (n) of sites in the catchment. Note that the event numbers on the x-axis differ between the plots, i.e. Event #40 does not refer the same event across all sites.

The Colpach catchment had more sites with no-flow responses during precipitation events with low soil moisture compared to precipitation events with higher soil moisture (Figure 6a). ~~However,~~ for few events with very high mean precipitation, all sites of the Colpach catchment had flow, mostly with a little delay. In the Foulschterbaach catchment all sites maintained flow for a first sequence of events, even with low soil moisture, while some of the sites fall dry during events with lower precipitation and intermediate soil moisture. Flow ~~was regained~~ at all sites when the normalised soil moisture reached a threshold of around 0.65. The Noumtemerbaach ~~showed a~~ gradual decline of flowing sites with a ~~corresponding~~ decline in soil moisture. Also, in this catchment, a sequence of average precipitation intensity events but rising soil moisture led to the activation of flow for all sites ~~in the catchment~~ (Figure 6: , Event# a). Also precipitation events with high intensity during periods of lower normalised soil moisture (<0.50) initiated ~~two~~ streamflow reactions (Figure 6c Events b and c)~~-~~. Subsequent events with soil moisture above that threshold led to the initiation of flow at all sites in the Noutemerbaach catchment. The Schammicht catchment is located in marl geology and monitored sites represent many small~~er~~ sub-catchments. Five series of precipitation events with high corresponding proportions of flowing streams were identified (Figure 6: Events g-h, i-j, k-l, m-n; o-p). Two of these series with the most subsequent precipitation events triggering flow responses ~~showed~~ relatively high soil moisture values (> 0.72 ;Events g-h, o-p), while a third period was associated with missing values and a very dynamic soil moisture, but successive events of higher mean precipitation compared to the average mean precipitation intensity in this catchment (Events k-l). Further, two short series of precipitation events (Eventss—i-j and m-n) of flow correspond to successive events of higher mean precipitation. It is worth noting that a single event of very high mean precipitation (60mm/h) did not lead to flowing conditions at all sites in the catchment ~~when soil moisture was low~~ (Event q). The temporal flow dynamics for the Beschruederbaach were generally closely related to those observed at the Schammicht catchment, as both catchments are very close to each other and have a similar geology and land use (Figure 1). The Hei catchment had rarely flowing conditions at both monitored sites. These flow responses mostly corresponded to either comparably high mean event precipitation and/or high soil moisture (> 0.8, Figure 6:). One site in the Pall catchment was located in the sandstone region while all others were situated in the marls (Figure 1). For this catchment, ~~share~~ of sites without flow ~~in~~ response ~~to precipitation events~~ is notably higher during times of lower soil moisture (Figure 6h Events r-u, v-x). However, in these dry periods, rapid flow activation ~~was introduced by~~ larger event precipitation (e.g. Events s-t and #w). Other periods with a higher number of sites having flow responses were linked to higher soil moisture (higher than 0.73). In the Schwebich catchment, the majority of the sites were located in the sandstone geology. Unfortunately, the share of "No-Data" observations w~~ere~~ quite significant during the first third of the events (Figure 6:). Nevertheless, there was a relation between ~~higher~~ soil moisture and ~~a high~~ proportion of sites with flow for the sites in the sandstone but ~~with less clear indication~~ compared to the marl and slate geology. Notable streamflow responses from the majority of the streams in the catchmeIred at comparably low soil moisture but a higher mean precipitation intensity during events d, e and f.

4.2 Random forest model results

4.2.1 Site selection

The evaluation criteria for a good model (sensitivity (correct flow predictions / total flow observations) and specificity (correct no-flow predictions / total no-flow observations) > 0.5) were not met for all sites. Th~~o~~se sites were excluded to avoid the inclusion of results with bad performing models in the further analysis. The site selection was based on a combination of the evaluation criteria (specificity and sensitivity) during validation. For 20 out of 23 sites in the marl region did the models meet the evaluation criteria~~ and had~~ a mean model accuracy of 0.84 ~~with~~ a standard deviation of 0.10 (Figure 7, Tab. S5-7). The sites were selected with datasets from all types of resampling methods (no resampling, over-sampling, over- and under-sampling). The three sites that did not ~~match~~ the evaluation criteria were the sites with the lowest number of observed precipitation events and had a notably unequal distribution of flow ~~to~~ no-flow responses (in case of site MA6, ~~even~~ only flow responses). These sites were located in the Schammicht and Pall sub-catchments (Figure 8). For four of nine sites in the sandstone, the models did not meet the evaluation criteria, with either very high sensitivity and very low specificity, or vice versa (Figure 7). These sites also had an unequal distribution of the flow responses (Figure 3). All of the sites ~~in the sandstone geology~~ were located on very small reaches and three of them on steep unpaved forest roads on the hillslopes (Figure 8). The mean model accuracy over all sites that ~~matched~~ the evaluation criteria was 0.79 (standard deviation: 0.12). All sites in the sandstone geology for which the models were acceptable had the best results with the over- and under-sampling approach. Eight out of 22 sites in the slate geology were rejected from further analysis based on the model evaluation criteria (Figure 7). After rejection of the unsuccessful models, the mean accuracy over all sites in the slate was 0.90 with a standard deviation of 0.08. The rejected sites in the slate geology were distributed over all sub-catchments (Figure 8). However, the Foulschterbaach catchment had a high share of sites (3 out of 5) that did not meet the evaluation criteria. All of the rejected sites in the slate geology had a low number of no-flow responses compared to the other sites in slate (Figure 3 and 7). In the case of SL5 and SL10, splitting of the dataset into training and test data led to zero samples of the no-flow class. For SL2 the ratio of 116:3 of flow to no-flow responses could not be compensated through the resampling of the data. Roughly two-thirds of the sites in the slate geology that selected for further analysis had better model performance for the resampled data.

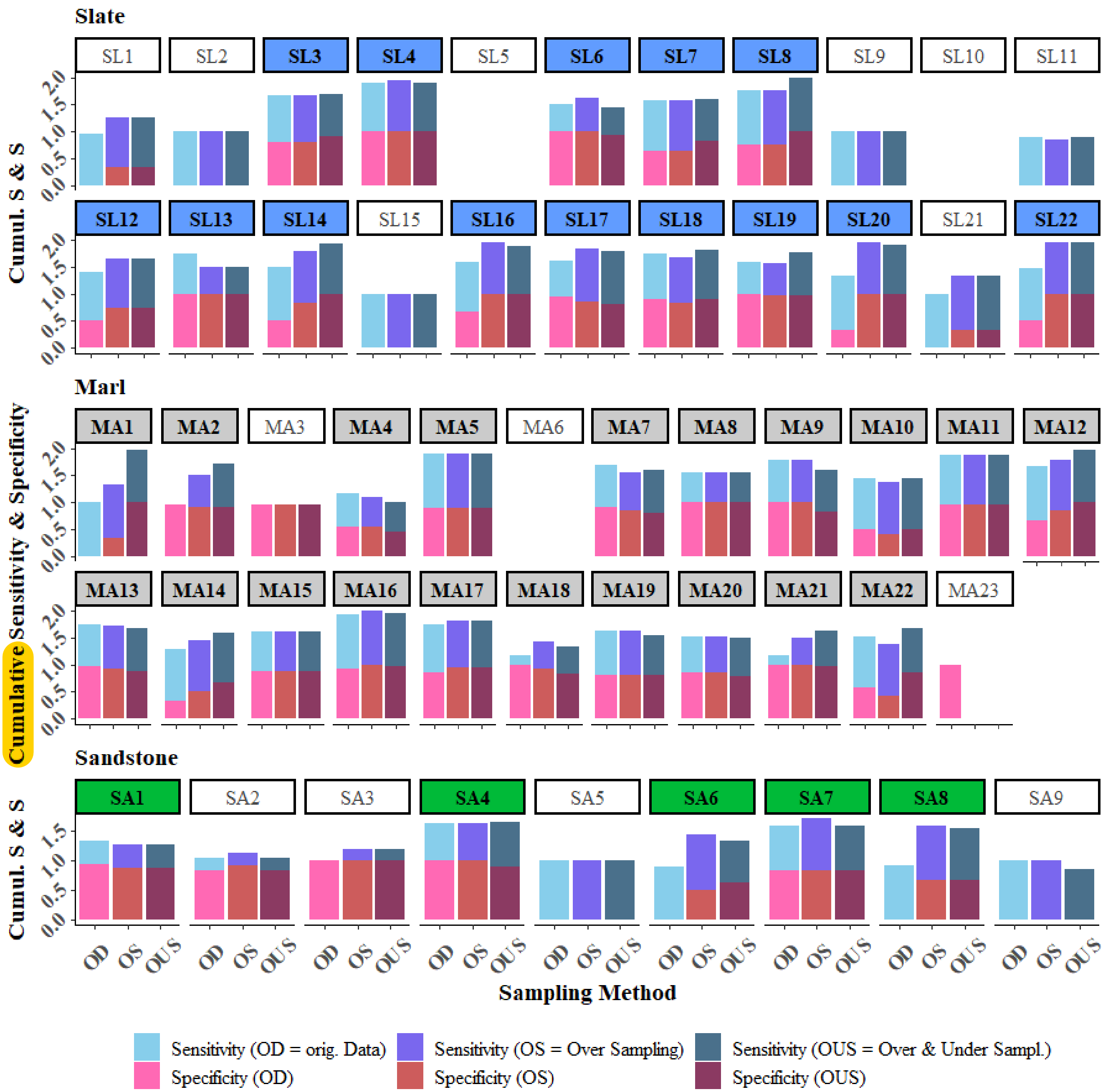

Figure 7: ~~Cumulative~~ sensitivity and specificity of the random forest models for the different sites using the ~~three data samples~~ original data (OD), oversampling dataset (OS), and over- and undersampling dataset (OUS). Sites that met the selection criteria for a good model fit are indicated with coloured boxes corresponding to the dominant geology in the catchment (blue = slate, gray = marls, green = sandstone). Sites that didn't meet the selection criteria were discarded for further analysis are indicated with non-colored boxes.

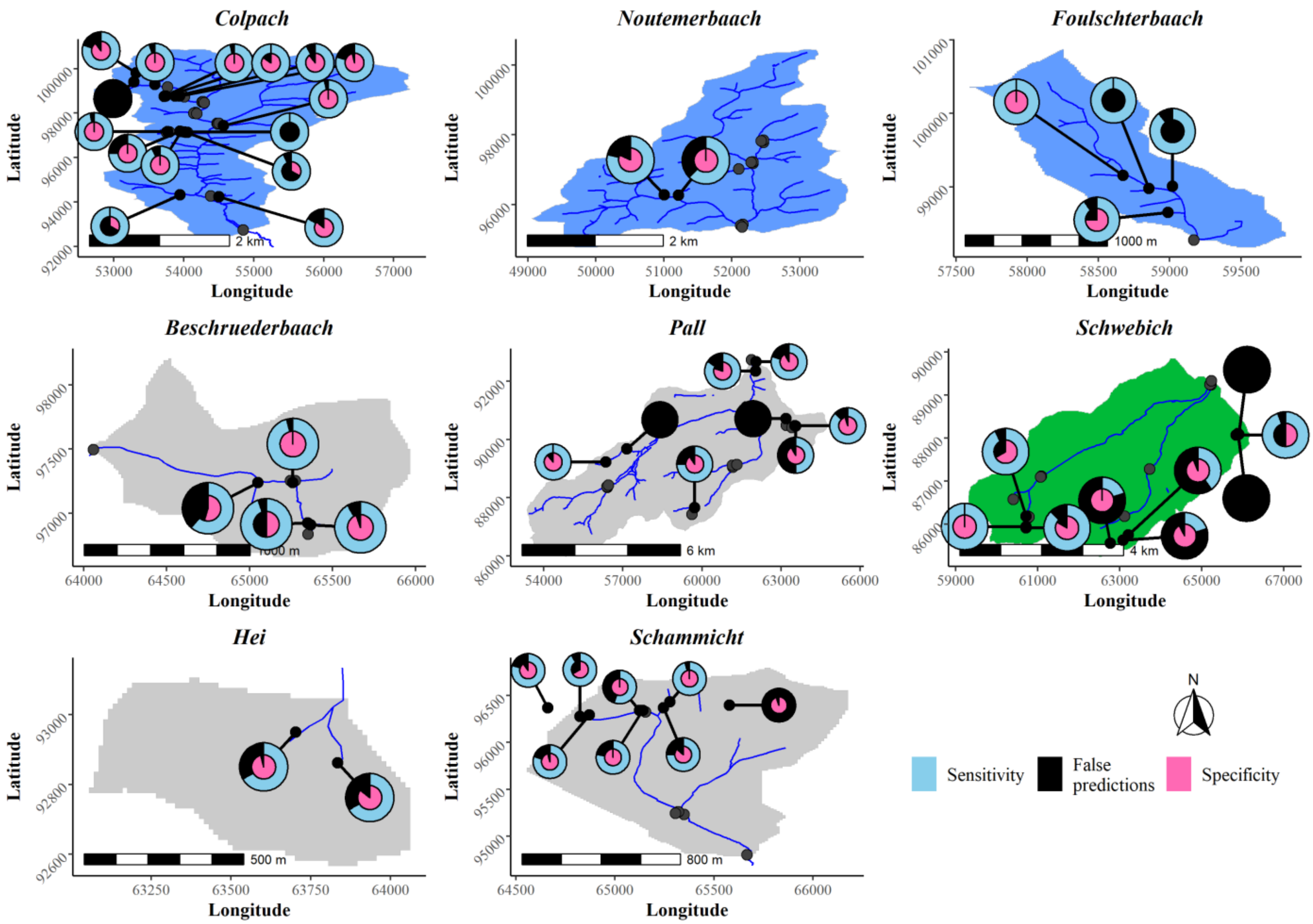

Figure 8: Sensitivity and specificity of the random forest models at the different sites in the sub-catchments (including the sites that did not fulfil the evaluation criteria). Both measures range from 0 to 1, thus the larger the proportion of the circle that is filled with colour, the better the model quality.

4.2.2 Predictor importance

The predictor importance ~~at each site~~ was defined by the ranked mean decrease Gini measure of the predictors in the site-specific model. The rank of a model predictor shows the relative importance in relation to the other predictors in the model with 10 as the highest rank of the 10 predictors (Figure 9). For the sites located ~~in~~ marl the soil moisture at 10 cm depth was ~~by far~~ the key predictor with the highest average rank (8.9) ~~–~~ being among the top three most important predictors for nearly all sites (Figure 9). ~~The~~ soil moisture at 50 cm depth was ~~ranked as~~ slightly less important with an average rank of 7.55, but was also among the most important predictors for almost of the sites. The API measures completed the highly important predictors with the ~~long-term~~ API_{14} measure being on average the second most important predictor (rank 8.05) having a slightly higher importance than the API_7 ~~measure~~. The top ranked predictors ~~included soil moisture and API and hence~~ represent either directly or indirectly the soil moisture conditions during the precipitation event. However, the correlations between the two API measures and ~~between~~ the two soil moisture were rather low (0.1 – 0.58) for the sites in marls, but ~~high~~ correlations were ~~indicated within~~ the two API measures API_7 and API_{14} (0.78 – 0-86) as well ~~as within~~ the soil moisture ~~predictors in~~ the two depths (0.15 – 0.75). While the precipitation measures (P_{mean}, P_{sum}, P_{max}) played only a minor role for three-quarters of the marl sites, the cumulative antecedent precipitation was ranked as important for two-thirds of the sites. The lowest average ranks (6.15) and the ~~a~~ wide sprea~~–~~ of ranks (3 - 10) for the minimum soil temperature in the marl geology compared to the other two geologies (6.6 and 7.93) are remarkable as is the low importance of the duration of a precipitation event (average rank 1.55), indicating that precipitation events of all duration were able to induce runoff responses in this geology. Sites on slate had similar patterns of predictor importance to those on marl (Figure 9). In contrast to the marl sites, ~~in the slate geology~~ the soil moisture at 50 cm depth was on average higher ranked (8.93) than that at 10 cm depth (8.71). ~~On average~~ both predictors were among the first two most important predictors for the majority of the sites on slate. Minimum soil temperature was the third key predictor in the slate region with two thirds of the sites having it as the third to first most important predictor. ~~Short and long-term~~ API was on average intermediate ranked (API_7: 5.5 and API_{14}: 6.29) ~~for the slate geology~~ with a variability of the ranks in a low~~er~~ to mid range (rank 1-8)~~-~~. Precipitation measures were among the second to fourth most important predictors (rank 8 and 9) only one -quater of the slate sites, while the duration of a precipitation event was not important for any sites on slate (average rank 1.71). The sites in the sandstone geology showed a more diverse patterns of predictor importance (Figure 9). Soil moisture at 10 cm and 50 cm w~~as~~ among the most important predictors for most of the sites in sandstone with ranks of nine and 10. The precipitation sum was very important for one site (rank 10) in the sandstone geology. Additionally, the precipitation sum was notably more important for the ~~other~~ sites on sandstone compared to the sites in the other geologies being on average the third most important predictor in the sandstone geology. Furthermore, mean event precipitation ranked high (rank 8) for two sites in the sandstone geology. Compared to the API_14 which was the only important antecedent precipitation measure at two sandstone sites, the API_7 and CAP had lower rankings. The importance of minimum temperature ~~in the sandstone~~ was with a average rank of 6.6 in the mid range compared to the other geologies. One of the two sites on sandstone with high ranks ~~of~~ precipitation duration (ranks 7 and 9) also showed a higher importance ~~of~~ other event precipitation measures (P_{mean}, P_{sum}, P_{max}) while these measures were not important for the other site. For all other sites in the sandstone geology, the duration of the precipitation event was ranked low.

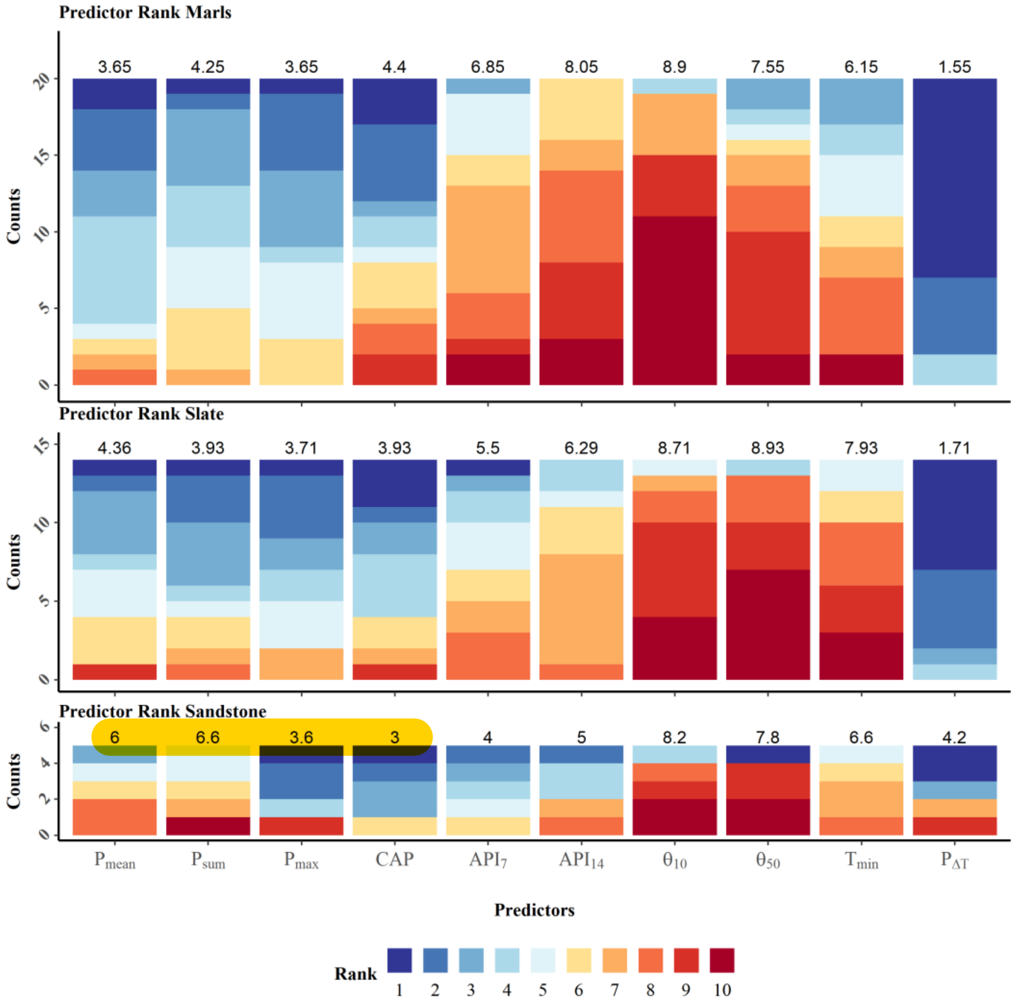

Figure 9: Rank of the parameter importance of each model predictor ~~at~~ the different sites counted in each geology. The rank is colour-coded, with the highest rank in red representing the most important predictor and the lowest rank in blue representing the least important predictor. The average rank of a predictor in each geology is indicated at the top of each bar.

5. Discussion

5.1 Factors affecting streamflow intermittency

The three main runoff generation mechanisms resulting in event streamflow are infiltration (Hortonian) overland flow, saturation excess overland flow and subsurface stormflow (Sidle et al., 1995; Zimmermann et al., 2014). The drivers that are involved in these processes are inputs of water to the system either in the form of rainfall or melt water (e.g. Horton, 1933; Weyman, 1973; Dunne and Black, 1970; Sando and Blasch, 2015; Tolonen et al., 2019). The ability of the system to buffer the incoming precipitation is limited by the infiltration capacity, ~~,~~the storage capacity and the antecedent soil moisture (e.g. Tromp-van Meerveld and McDonnell, 2006; Bachmair and Weiler, 2014; Stewart et al., 2019; Gutierrez-Jurado et al., 2019; 2021; Warix et al., 2021). This study reveals that the average soil moisture was significantly different for ~~precipitation~~ events that resulted in flow, and those without flow response~~s~~ (Figure 4). This was the case for the sites on all three geologies. Additionally, the antecedent precipitation (7 day and 14 day API) was important for the marl and slate ~~geologies~~. The high potential to distinguish the two classes of flow responses by soil moisture is confirmed by the high importance of the corresponding predictors in the random forest models (Figure 9). The event analysis in this study indicates a seasonal timing (Figure 6) and thresholds (Figure 4) of soil moisture at which streamflow is initiated. Times of low or high soil moisture and respective ~~responses of~~ no-flow or flow roughly follow the seasonal fluctuations in evapotranspiration. Thus, in the winter months with higher soil moisture, a succession of multiple precipitation events with flow responses are more common than in the summer months with lower soil moisture (Figure 6). Annual variations of streamflow in temperate regions are usually explained by the seasonal fluctuations of evapotranspiration which affects the soil moisture conditions of the catchment (e.g. La Torre Torres et al., 2011; Penna et al., 2011, 2015; Trancoso et al., 2016; Zimmer and McGlynn, 2017). The importance of those seasonal fluctuations on streamflow initiation in the Attert catchment is underlined by the lower precipitation (26 mm to 30 mm of average event precipitation sums) during the "wet" periods with higher soil moistures compared to the higher precipitation sum during the "dry" periods (43 mm to 50 mm of average event precipitation sums; see Figure 6). The seasonal variations ~~of~~ soil moisture are visible in all geologies of the catchment. This seasonality is more pronounced for the catchments on slate and marls, while ~~in the sandstone~~ half of the sites were dependent on soil moisture ~~while~~ the other half were dependent on the precipitation characteristics. The lower dependency of flow responses on soil moisture at sites on sandstone potentially indicate that other sources like deeper storage, local and perched groundwater has a ~~higher~~ influence on the streamflow responses than in the other geologies. ~~The~~ prolong~~u~~ed supply of streamflow by local, perched groundwater tables on sandstone ~~geologies~~ above less permeable layers was shown to control streamflow intermittency in a Mediterranean (Guieterrez-Jurado et al., 2019; 2021) and on slate in a subtropical, humid climate (Zimmer and McGlynn 2017). In contrast the large differences in soil moisture between flow and no-flow responses at sites on marl as well as the larger volatility of active sites in catchments with marls indicate a faster saturation of the soil with quicker and shorter SOF responses.

Besides the seasonal variation, soil moisture can increase rapidly in reaction to precipitation events. These fast increases in soil moisture ~~were supporting~~ streamflow responses also during the dry periods. Streamflow responses to these dynamically increasing soil moisture values were mainly observed for the marl sites (Figure 6). A majority of the sites in marl sub-catchment had streamflow responses during these short liv~~ing~~ phases of ~~risen~~ soil moisture, while the effect was less pronounced on slate and sandstone. The importance of soil moisture in both soil depths in the marl geology is reflected by the results of the random forest model which ranks those predictors and the API the highest (Figure 9). The importance of soil moisture in the system is in line with the findings of Kaplan et al. (2020) who identified catchment area and curvature, which are surrogates of the topographic wetness index, as the two ~~crucial~~ predictors in the spatial model of streamflow intermittency. Topography, hydraulic conductivity and transmissivity as well as the water storage capacity of a catchment defined by bedrock geology and soil type ~~were~~ identified as dominant predictors for streamflow timing and the spatial dynamics of the intermittent stream network in different climates and topographies (e.g. Tanaka et al., 2005; Jencso and McGlynn, 2011; Sando and Blasch, 2015; Ward et al., 2018; Prancevic and Kirchner, 2019; Gutiérrez-Jurado et al., 2019; 2021; Kaplan et al., 2020; Shanafield et al., 2020). The dependency of streamflow intermittency on seasonal dynamics of evapotranspiration as found in this study was also reported for a catchment with sub-tropical humid climate and rather ~~homogenious~~ precipitation sums and associated with the catchment storage ~~state~~ (Zimmer and McGlynn, 2017). These changes in catchment storage were reported to change the streamflow contributions from shallow, perched groundwater dominated runoff production during dryer periods with low storage ~~states~~ to deeper groundwater that was rising into the contributing soil layers at higher storage ~~states.~~

The importance of the event precipitation measures (P_{max}, P_{mean}, P_{sum},) was surprisingly low. This may result from the small share of precipitation events exceeding the infiltration capacity ~~in~~ all geologies (Demand et al., 2019) and thus limiting the probability for Hortonian overland flow. Gutierrez-Jurado et al. (2019) simulated intermittent streams ~~on~~ different soil types and demonstrated that HOF was the dominating streamflow contribution on sandy loam soils with low hydraulic conductivity. Soils with the lowest hydraulic conductivity in the Attert catchment located on marl~~, however the~~ soils are very heterogenious and higher effective hydraulic conductivity ~~was observed in various studies~~ (e.g. Demand et al., 2019; Kaplan et al., 2020). Strong influence of precipitation characteristics on the ~~appearance~~ of intermittent streamflow ~~were~~ also observed in humid tropical climate (Zimmermann et al.; 2014) or in arid climates (Ries et al., 2017) with large seasonal or spatial variability in event precipitation sums. ~~This variability in precipitation is reflected by precipitation characteristic related predictors having a high explanatory power of streamflow initiations in these climates.~~ In contrast, precipitation related predictors become less important in situations where ~~strong influence of~~ the fluctuations ~~of~~ soil moisture or groundwater ~~inputs~~ control saturated conditions and the associated SOF and SSF, because the high importance of predictors like groundwater, soil moisture and antecedent precipitation will ~~superimpose~~ the importance of precipitation (Wrede et al., 2014; Ward et al., 2018; Jensen et al., 2019; Gutierrez-Jurado et al., 2021).

~~Generally,~~ the impor~~a~~tance of precipitation event characteristics may also result from the definition of the precipitation event and the temporal resolution of the data. Zimmer and McGlynn (2014) identified the interannual variability of evapotranspiration as the major driver of stream network dynamics while they report variable storm intensity during a single precipitation event period. In their study precipitation events are defined as two events separated by at least 12 hours and > 8 mm of precipitation while in this study the events need to be separated by 3 hours and had a minimum precipitation of 1 mm. This implicates that a single precipitation event in our study ~~has potentially lower sums but~~ would be potentially merged to one large event according to the definition of Zimmer and McGlynn (2014). This effect becomes even stronger in the study of Jensen et al. (2019) who separated precipitation events by a minima~~l~~ period of 24 h without rain. They found 16% of the variance ~~of~~ stream network exten~~d~~ explained by precipitation characteristics. With our precipitation event definition, the variability between precipitation events may be~~come~~ less pronounced, but the assignment of a specific precipitation event to a streamflow response and the associated state of soil moisture ~~at that time may~~ ~~has a~~ more precise and thus, soil moisture becomes more relevant compared to the precipitation event characteristics. Event definitions that support prolonged periods of multiple precipitation events as one event hamper the identification of the actual precipitation that triggered the streamflow response. Thus, the characteristic of the precipitation event gains in relevance because it potentially has “pre-event precipitation” ~~sub~~merged within the actual event. This also means that pre-event saturation measures (e.g. API / soil moisture) ~~close~~ before the triggering precipitation event may be~~come~~ less relevant, as this information is partially included in the event precipitation ~~of~~ the entire period.

5.1.1 Factors affecting streamflow responses for sites onmarl geology

The soils in the marl geology have the highest hydraulic conductivity in the Attert catchment (Demand et al., 2019). However, the underlying marl ~~geology~~ is characterised by a low permeability (Wrede et al., 2014). Beiter et al. (2020) analysed the interaction between precipitation events, local groundwater and streamflow responses in the sub-catchments Beschruederbaach and Schammicht, ~~which are located in the marl geology~~ (Figure 1). They found that after a dry period ~~strong transmissivity feedback of event precipitation through the local groundwater to the~~ streamflow response were possible after only few precipitation events that raised the groundwater level to a threshold level near the surface. Below that threshold the dynamics of groundwater and streamflow were less synchronised. For lower antecedent soil moisture conditions, they found a change towards higher incidences of overland flow and runoff contributions through preferential subsurface flow paths during precipitation events. Also, Wrede et al. (2014) linked the fast responses of event water in the Wollefsbach catchment – a sub-catchment in the marl region of the Attert catchment – to lateral subsurface flow of pre-event water and contributions of event water through preferential pathways. This process is accompanied by saturation-excess overland flow during periods of higher saturation (Wrede et al., 2014). They assume that the deeper groundwater table does not raise above the highly impermeable boundary layer even during the wet season, while the stream ~~was~~ ceas~~ing~~ flow during the dry season without major streamflow responses during storm events. Wrede et al. (2014) describe the streamflow responses on marls as flashy which also agrees to the fasted response times for the streamflow responses in the event analysis (Figure 4f). During low catchment storage ~~states~~ a fast expansion of the stream network followed by a quick but lagging saturation of the upper soil as described by Jensen et al. (2019) may sustain short-liv~~ing~~ streamflow responses during the dry period. In contrast, during the dormant season a perched saturated zone above the less permeable soil layer as described by Gutierrez-Juardo et al. (2019) may develop~~s~~ and sustain~~s~~ the streamflow in the intermittent streams. The findings of Demand et al. (2019) and Beiter et al. (2020), combined with the strong dependenc~~y~~ of streamflow initiation on soil moisture as indicated by the random forest model, suggest that saturation excess overland flow and shallow subsurface stormflow are ~~among~~ the dominant processes controlling the streamflow responses in the marl ~~geology~~. This finding is supported by the importance of the 14-day API, which indicates an increased probability of streamflow initiation and continuation following larger antecedent precipitation. Demand et al. (2019) also analysed precipitation events ~~of~~ a time period overlap~~ping~~ with the one in this study and found no events exceed~~ing~~ the infiltration capacity of the soil matrix for sites ~~located~~ in the forests. This finding is in accordance with the low importance of all precipitation measures in the models for sites located in the marl region, which were predominantly forested. This suggests, that in case the shallow storage system becomes saturated, smaller and larger precipitation events can trigger SOF and this hinders the random forest models to split the dataset based on the precipitation characteristics leading to the low importance of these predictors.

Soil temperature ~~showed high~~ importan~~ce~~ in the random forest model for the majority of sites in the marl geology (Figure 9). This underlines the dependency of flow initiation on the seasonal changes ~~of~~ temperature and evapotranspiration in the Attert catchment, which were also found in other temperate catchments (Wrede et al., 2014; Zimmer and McGlynn, 2017). Overall, the models showed a good ability to separate flow and no-flow responses by soil moisture and temperature data, indicating shallow sub-surface storm flow and saturation excess overland flow in the marl geology.

5.1.2 Factors affecting streamflow responses on slate geology

The most important model predictors for the sites on the slate are soil moisture in the upper and the lower soil layer followed by temperature and the API measures, while precipitation related predictors play a minor role (Figure 9). The soil moisture at 50 cm depth ~~is~~ slightly more important than soil moisture at 10 cm depth ~~at~~ several ~~of the~~ sites. This can be caused by the high fraction of preferential flow paths in the clay-rich soils ~~as frequently found~~ in the forested regions in the slate geology of the Attert catchment (Demand et al., 2019). This would allow event water to travel quickly into deeper soil layers and to trigger sub-surface storm flow. This hypothesis is supported by the higher mean soil moisture in 50cm depth ~~compared to those in~~ 10 cm depths ~~at~~ which flow and no-flow responses were separated by the random forest models at most of the sites (Fig. S9). Additionally, slate bedrock is – ~~as~~ the layers of low permeability in marl - relatively impermeable but in contrast to ~~those layers in~~ marl the bedrock – soil interface in slate is rather fractured and soil depths ~~to bedrock is~~ deeper (>50cm, Demand et al., 2019). Previous studies in the Weierbach catchment – a sub-catchment of the Colpach catchment that also shows intermittent streamflow (Figure 1) highlighted the presence of a "fill and spill" mechanism of subsurface stormflow based on the isotopic signature of the streamflow and local groundwater observations (e.g., Wrede et al., 2014; Martínenz-Carreras, 2016; Beiter et al., 2020). ~~.~~ This mechanism appears when depressions at the bedrock surface have to be filled until water spills over the bedrock relief (Tromp-van Meerveld and McDonnell, 2006). It leads to a distinct precipitation threshold that has to be reached to ~~trigger~~ strongl~~y~~ enhanced subsurface stormflow ~~in their study area~~. For the Weierbach catchment, this mechanism ~~was identified as inducing~~ double peak streamflow when the catchment storage ~~state~~ reaches a certain threshold during the dormant season or after intense precipitation events in the dry season (Martínenz-Carreras, 2016). The dependency of the streamflow responses on the seasonal variations of the temperature and evapotranspiration which ~~are~~ influenc~~ing~~ the catchment storage state is also supported by the importance of temperature as a predictor in the random forest model. Single peak streamflow events occur below the threshold from direct precipitation ~~i~~nto the stream channel and saturation excess overland flow in the riparian areas (Martínenz-Carreras, 2016), but also partly by subsurface stormflow through macropores and fractures on the hillslopes which are connected to the saturated riparian areas (Angermann et al., 2017; Jackisch et al., 2017). Th~~is~~ rather direct inputs to streamflow through the shallower soil layers during the dry season were connoted with hillslope contributions

(Martínenz-Carreras, 2016). This may ~~result in~~ the importance of soil moisture in the upper soil layers (10cm depth) for the intermittent streams in this storage state. During the wet season, catchment storage at the plateaus on top of the hillslopes become active and contribute~~s~~ via subsurface stormflow and shallow groundwater (Martínenz-Carreras, 2016; Schwab et al., 2017; Beiter et al., 2020). This shift from the dry to wet state of the system and the activation of flow through deeper soil layers may explain the higher importance of the soil moisture in 50 cm depth for the activation of the majority of streamflow responses in the intermittent stream network on slate. Although the soil moisture dynamics do not allow to draw direct conclusions ~~to~~ groundwater dynamics, local groundwater tables in the slate catchments were found between 0.5m to 3m depth and were synchronis~~ing~~ with the soil moisture dynamics in the unsaturated zone above certain thresholds during the wet season (Martínenz-Carreras, 2016). ~~The~~ high~~er~~ variability and strong~~er~~ intermittency of streamflow during the dry season with hillslope contributions as the predominant source of streamflow and the reconnection of the stream network with the onset of groundwater contributions in the wet season ~~was also~~ observed and modelled by Ward et al. (2018) and Warix et al. (2021). Site SL12 is the only site on slate with low importance of soil moisture (Figure 9, θ_{10} and θ_{50} in blue colors rank 4 and 5). This site is located in the Foulschterbaach catchment (Figure 1), where the majority of the sites did not match the evaluation criteria for the model selection (Figure 8) and soil moisture was not representative for the catchment (detailed discussion in section 5.2).

5.1.3 Factors affecting streamflow responses on sandstone geology ~~sandstone~~

Sandstone~~ layers~~ are generally characterised by a high permeability which provides a large aquifer storage that feeds permanent springs (Colbach, 2005). The high infiltration capacity limits surface runoff during precipitation events (Wrede et al., 2014). In fact, identifying monitoring sites with a regular intermittency of streamflow was challenging (Kaplan et al., 2019). As intermittent streamflow in the sandstone is less common and the relatively low number of initial sites in this geology had to be reduced after the model evaluation (Figure 7), a general pattern of typical controls of intermittent streamflow in this geology could not be identified. Thus, the predictor importance and the potential controls o~~f~~ streamflow intermittency are discussed at the site scale rather than ~~at the scale of~~ the entire geology.

The sites SA5 and SA9 were quasi-perennial and the number of events showing no-flow was too small for a balanced class representation in the random forest model. However, site SA6 (fig. 1), which was located downstream of the two springs feeding the reaches at SA5 and SA9~~. This site shows a strong~~ dependence on soil moisture, the duration of precipitation events and the antecedent precipitation. This indicates that either a specific soil moisture threshold or ~~that~~ a long period of precipitation is required to produce streamflow and to compensate the transmission losses. This type of flow cessation through transmission losses ~~was~~ reported for small catchments with low or moderate channel gradients and coarse sediments (e.g. Constantz et al., 2002; Costa et al., 2013). Streamflow in the perennial streams in the Luxembourg sandstone were associated with the contributions of a large aquifer that provides the necessary storage to sustain ~~highly~~ continuous baseflow ~~rates~~ (Wrede et al., 2014). However, in the case of intermittent streams the existence of shallow perched groundwater storages that develop at the boundary layer between less permeable geology and the overlying permeable sandy geology as described by Gutierrez-Jurado et al. (2019 and 2021) are likely the source for streamflow at the sites SA5 and SA9.

Sites SA7 and SA8 are located in the marly zones at the foot of sandstone hillslopes (Fig. 1). Both sites may acquire flow from nearby groundwater springs which are also used for drinking water. The two sites also share the same important model predictors: soil moisture ~~in~~ both depths and temperature. At these sites, the controls on flow cessation during dry periods can either relate to natural controls caused by seasonal fluctuations of soil moisture and transmission losses in the marl layer, or can be amplified by higher rates of water withdrawal ~~in the wells~~ during summer ~~seasons.~~ This kind of anthropogenically induced alteration of streamflow intermittency has been reported for many rivers (Chiu et al., 2017).

The most important predictors for site SA4 were soil moisture ~~in~~ the two depths followed by maximum precipitation intensity and precipitation sum. The geological setting characterised by marls in the upstream part and sandstone in the lower part of the catchment may influence streamflow at this site. In contrast to the other sites, which show a high importance of soil moisture, the streamflow response of SA4 is always flashy with longer events during periods of high soil moisture ~~saturation.~~ The predictor ranks of maximum and cumulative event precipitation are also comparably high at this site (Rank 7 and 8), indicating that large precipitation events are needed to compensate for the transmission losses through the sandy streambed. This assumption is supported by the regularly ceasing streamflow 100 to 150m downstream of the gauging ~~point~~ (Fig. 1) which is also indicated in the topographic map of the region (Le Gouvernement du Grand-Duché de Luxembourg, 2009).

The stream channel at the site SA1 is characterised by a steeply inclined logging track. The most important predictors at this site are precipitation sum and maximum precipitation intensity, while mean precipitation intensity and cumulative antecedent precipitation and soil moisture are less important predictors. This is a clear indication for infiltration excess overland flow being the main process at this site. This contradicts the findings of Wrede et al. (2014) who considered infiltration excess overland flow to not be a relevant process in the sandstone sub-catchment of the Attert, Huewelerbaach. The different result at SA1 might result from the specific setting, where a logging track had been eroded down to the bedrock. Notable traces of finer sediment were found at the flow tracks at the foot of the hillslope which potentially caused ~~week forms of~~ clogging similar to that described by Shanafield et al. (2020) for intermittent streams crossing different geologies. The most likely reason for the initiation of HOF are the high precipitation sums during the events and the steep slopes of the tracks as similar conditions were observed to cause HOF on steep slopes in a sandstone catchments (Scherrer and Naef, 2003; Tanaka et al., 2005; Gutierrez-Juardo et al., 2019; 2021).

5.2 Uncertainties of event analysis and random forest model

This study relied on the availability of precipitation, soil temperature and soil moisture data. The event classification was based on two assumptions: a) snow can be neglected and b) every flow response is induced by a rainfall event. Misclassification of the events could happen ~~if~~if (1) precipitation occurs as snowfall delaying the flow response (e.g. Floyd and Weiler, 2008), (2) water in the channel ceases to flow during a period of temperatures below zero (Tolonen et al., 2019) so that the flow response is not related to a precipitation event and thus ignored by the event analysis or (3) inaccuracies or gaps in the streamflow observations, as described by Kaplan et al., 2019. However, scenarios (1) and (2) occur only for short timespans in the studied period and the streamflow data from time-lapse photography was carefully quality checked. The occurrence of snowfall and frozen water in the channel was validated by the time-lapse images from which the binary streamflow information was obtained (Kaplan et al., 2019). Freezing and thawing of water in the channel was only the main control of flow cessation and reactivation at the sites MA6, SL21 and potentially influenced the flow responses of SL2 and SL5 (Figure 3). These sites were rejected by the model evaluation procedure.

Uncertainty of the models can also arise from simplifications or misrepresentation of the predictor data. Soil moisture is highly heterogen~~i~~ous in space and time. The approach of using averaged soil moisture~~s of~~ multiple sites per geology tries to overcome this spatial ~~and temporal~~ heterogeneity ~~by representing the general trend of soil moisture in the catchment~~. The temporal sucession of infiltration signals along the sensors in the three depths (10, 30 and 50 cm) was used by Demand et al. (2019) to differenciate between infiltration processes at the plot scale. However, at the scale of a geological unit the dynamic of soil moisture did not differ as significant ~~between~~ all depths, ~~resulting in discarding~~ the soil moisture ~~in~~ 30 cm depth. While the ~~whole time series of~~ soil moisture ~~in~~ 10 and 50 cm depth ~~had no high correlations~~, the soil moisture measures at the event scale extracted for each site ~~showed~~ high correlat~~ions~~ for some sites (fig. S6-S8). Limits in the representability of geology wide soil moisture were revealed at the sites of the Foulschterbaach catchment where soil moisture and antecedent precipitation indices ~~had very low correlations~~. All sites in the Foulschterbaach have a lower total number of events due to a delayed installation (Figure 5), but the reason for poor model ~~results~~ most likely ~~result from~~ non-representative soil moisture data (See also section 5.1.2). Mälicke et al. (2020) identified rainfall and the seasonal dynamics of evapotranspiration as the two major controls of soil moisture in the Colpach catchment. While the seasonal component is expected to be similar in the Colpach and the Foulschterbaach catchment, soil moisture responses to rainfall differ (Figure 6). Despite the weak representation of soil moisture in this catchment, the value of the general soil moisture dynamics in a catchment geology over the proxy variable API is underlined by the predictor importance of soil moisture in the random forest models. It may be possible that a better representation of the soil moisture dynamics through API can be reached by extending the represented precipitation periods to 30, 64 or 128 days as ~~i.e.~~ used by Zimmermann et al. (2014) or Jensen et al. (2019). However, it needs to be investigated which parametrisation of the API measure fits best for a certain geology or soil type to adequately represent the soil moisture dynamic.

Cases where the random forest models were not ~~cap~~able to represent flow responses correctly, were usually caused either by a small test dataset (Ließ et al., 2012) or an imbalance of the modelled classes (Lunardon et al., 2014) and in the Foulschterbaach watershed potentially also by the differences between the locations where the predictor data (soil moisture and temperature) were collected and the locations of the gauging sites (i.e. the response variables). The misrepresentation of the soil moisture in the Foulschterbaach catchment by the soil moisture obtained in the Colperbach catchment is supported by the very low correlation between the API and soil moisture ~~values~~ for the sites in this catchment~~.~~).

The comparison between the mapped event responses (Figure 5) and the model specificity and sensitivity (Figure 8) reveals that the number of events has a ~~major~~ effect on the accuracy of the model. Sites with low numbers of events ~~where this is likely to have an impact are the sites~~ MA3, MA23, SA2 and SA3 (Figure 3). The flow responses classes at the sites SL1 and SL15 (both in the Colpach sub-catchment) were highly imbalanced with significantly more flow (> 100) than no-flow responses (4 - 10). This reduced the likelihood to select a representative dataset for the training datasets for these sites. The class imbalance is generally a major problem of all statistical approaches and for those sites that cannot be adequately represented due to small datasets. If resampling approaches as used in this study are not able to balance out the classes ~~only~~ longer study periods with additional events ~~are capable~~ to overcome this drawback. In cases where the classes are well balanced and sufficient events are available but the model has still a low performance it might be an indication that either the data ~~is~~ not match~~ing~~ or alternative predictors are needed to describe the modeled dependencies.

Overall, the model accuracy was generally quite high (geology averages from 0.79 – 0.90) for the selection of models used in the predictor importance analysis. The models for a majority of the sites had excellent performance in predicting flow and no-flow responses with the test-dataset leading to high values of cumulative sensitivity and specificity close to the maximum of 2 (Figure 7). Despite the good predictions at the sites with the test data, model transfer~~s~~ between sites is not possible to the site specific statistics of each random forest. Generally, the random forest approach and the selected predictors were capable to predict the flow responses at most of the sites. However, for future studies it would be interesting how different event definitions would affect the outcome of model predictor importance and if additional event based predictors would allow for even higher accuracies of the models. The inclusion of spatial and event based predictors in future models can provide further interesting insights into the temporal and spatial dynamics of the intermittent stream network. Recent advances of modelling approaches show promising results (Gutierrez-Jurado et al., 2021; Botter et al., 2021). Ultimately, the model selection has to be tailored to the available data as

data imbalance will remain as a challenge for future studies chosing random forest or other statistical approaches.

Uncertainty may also arise from the variation ~~of~~ the catchment sizes. According to the findings of Kaplan et al. (2020), catchment size is among the strongest spatial predictors of intermittent streamflow occurrence in space in the Attert catchment, thus superimposing the effect of geology. The catchments included in this study have a notable range in ~~catchment~~ size ~~in~~ each geology ranging between 450m² and 734~~.~~223m² (Figure S1). Catchment size was not included in the analyses when the importance of model predictors at each site were compared to the other sites on the same geology. However, there was no significant correlation between catchment size and parameter importance or mean decrease Gini (Figures S11, S12, S13).

6. Summary and conclusions

This study provides insight into the characteristics of rainfall events that either do or do not trigger a streamflow response in intermittent streams in watersheds with a temperate climate. The results underline that controls on intermittent streamflow depend on the geological setting of the catchment. The main findings are summarised as follows:

(1) The classification of precipitation events into “flow” and “no-flow” responses provided an appropriate basis for further analysis in a random forest model. The random forest model was applied ~~for each site~~ to model flow response classes based on the predictors of precipitation characteristics (P_{mean}, P_{max}, P_{sums} and P_D), antecedent precipitation indices (7 and 14-day API), maximum soil moisture at two depths (θ_{10} and θ_{50}) and minimum soil temperature. For the majority of the random forest models, maximum soil moisture during the precipitation event was identified as the main temporal control that could explain the streamflow response.

(2) The controls of streamflow responses to precipitation events differed for the three geological regions. In regions characterised by marl geology the ~~pre~~dominant controls were soil moisture in the top soil layer followed by antecedent precipitation, soil moisture in the deeper soil layer and soil temperature, suggesting saturation excess overland flow ~~are~~ the most important processes for streamflow generation, ~~which are governed by the overlaying seasonal fluctuations in evapotranspiration~~. A soil layer of very low permeability ~~in~~ 20 to 50 cm depth~~s~~ may support the development of shallow, perched groundwater on marls during the wet periods which contributes to streamflow. For the slate regions, soil moisture in the lower soil layer constitutes a slightly stronger predictor than soil moisture in the upper layer and also the average splitting values of the the lower soil moisture values in the random forest models were higher for most sites on slate. This finding corresponds with results from earlier studies that hypothesised shallow subsurface flow during the dryer periods and a fill and spill mechanism at the ~~subsurface topography~~ during the wet periods ~~as~~ the dominant control of streamflow generation in the slate region of the Attert. The marl and slate geologies share the importance of the temperature predictor which is interpreted as ~~the~~ indicator of seasonal changes in evapotranspiration ~~which~~ is ~~a~~ known control of the storage dynamics in the Attert catchment.

Overall, soil moisture was the most prominent predictor for intermittency in the random forest models for the sites in the sandstone region in this study. However, a detailed evaluation of site ~~location~~ in the sandstone regions revealed either parts of marl geology in the contributing area or the presence of permanent springs, which are likely to be located at the marl-sandstone boundary. In both cases streamflow intermittency is likely caused by transmission losses. Only one site, which might be the most representative site for stream flow intermittency in sandstone, showed ephemeral streamflow controlled solely by precipitation and infiltration excess overland flow. Due to the limited number of sites with intermittent streamflow in the sandstone geology, no overarching pattern of streamflow controls could be identified.

The combined dataset of intermittent streamflow observations, precipitation, soil moisture, and soil temperature and the methodology of using classified events in a random forest modelling approach allowed us to identify characteristic controls of streamflow intermittency in the marl and slate geologies. Overall, the results of this study highlight the importance of soil moisture and temperature as controls of intermittency in a temperate climate and the different controls in the three geological settings. Future studies ~~may~~ increase the understanding of the spatio-temporal controls of streamflow intermittency by analysing it at geological boundary zones in the headwater catchments of the temperate climates.

Code and data availability

Data and the analysis code are available from the authors upon request.

Author contributions

NHK installed the monitoring network of time-lapse cameras, prepared the data, designed the analysis and carried it out. TB and MW designed the overall study and the sensor cluster monitoring network. NHK prepared the manuscript with contributions from the co-authors TB and MW.

Competing interests

The authors declare that they have no conflict of interest. Markus Weiler and Theresa Blume are editors of the journal.

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