A multi-scale study of the dominant catchment characteristics impacting low-flow metrics

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Abstract
Low flows can impact water use and instream ecology. Therefore, reliable predictions of low-flow metrics are crucial. In this study, we assess which catchment characteristics (climate, topography, geology and landcover) can explain the spatial variability of low-flow metrics at two different scales: the regional scale and the small headwater catchment scale. For the regional-scale analysis, we calculated the mean 7-day annual minimum flow ($q_{min}$), the mean of the flow that is exceeded 95% of the year ($q_{95}$), and the master recession constant ($C$) for 280 independent gauging stations across the Swiss Plateau and the Swiss Alps for the 2000–2018 period. We assessed the relation between 44 catchment characteristics and the three low-flow metrics based on correlation analysis and a random forest model. Low-flow magnitudes across the Swiss Plateau were positively correlated with the fraction of the area covered by sandstone bedrock or alluvium, and with the area that has a slope between 10° and 30°. Across the Swiss Alps, low-flow magnitudes were positively correlated with the fraction of area with slopes between 30° and 60°, and the area with glacial deposits and debris cover. There was good agreement between observations and predictions by the random forest regression model with the top 11 catchment characteristics for both regions: for 80% of the Swiss Plateau catchments and 60% of the Swiss Alpine catchments, we could predict the three low-flow metrics within an error of 30%. The residuals of the regression model, however, varied across short distances, suggesting that local catchment characteristics affect the variability of low-flow metrics. For the local-scale headwater catchments, we conducted 1-day snapshot field campaigns in 16 catchments during low-flow periods in 2015 and 2016. The measurements in these sub-catchments also showed that areas with sandstone bedrock and a good storage-to-river connectivity had above average low-flow magnitudes. Including knowledge on local catchment characteristics may help to improve regional low-flow predictions, however, not all local catchment characteristics were useful descriptors at larger scales.

KEYWORDS
discharge, hydrologic drought, landscape properties, machine-learning, recession, spatial variation

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Low river flows impact human activities and riverine ecosystems that depend on river discharge or stage (Bradford & Heinonen, 2008; Lake, 2003; van Vliet et al., 2011). After several recent droughts, there are increasing calls for improved low-flow management across Europe (Stahl et al., 2016; Van et al., 2016; Wada et al., 2013). Switzerland depends on stream water for household and industry use, river transportation, hydropower generation, irrigation, and in mountain areas for production of artificial snow (Blanc & Schädler, 2013; Wehren et al., 2010). Therefore, low flows in rivers may have large economic impacts.

A prerequisite for improved management of low flows is to understand the variability in low-flow properties, and the causes and drivers of this variability. Low flows are caused by climatic variations, mainly low precipitation, high evapotranspiration, or freezing conditions (e.g. Dierauer et al., 2018; Florianicic et al., 2020; Florianicic et al., 2021; Kormos et al., 2016; Teuling et al., 2013), but their magnitude also depends on catchment characteristics, like geology, soil properties, or topography (Florianicic et al., 2019; Li et al., 2018; Price et al., 2011; Staudinger et al., 2017). Thus, the expectation is that low-flow metrics can to some degree be predicted from the spatial distribution of these catchment characteristics and climate (e.g. Burn et al., 2008; Kennard et al., 2010; Laaha & Blöschl, 2006).

Several approaches have been used to derive regional maps of low-flow metrics based on catchment characteristics, including catchment grouping or regionalization of flow duration curves (e.g., Booker & Sneider, 2012; Boscarello et al., 2016; Castellarin et al., 2004; Laaha & Blöschl, 2006; Santos et al., 2018; Sauquet & Catalogne, 2011). Sneider et al. (2013) used random forest models to relate catchment characteristics to flow intermittence (i.e. the presence of no-flow periods in rivers) across France. Although the overall predictive performance of these models was not convincing, they revealed significant relationships between landscape characteristics, such as catchment size, shape and slope, and stream intermittence. Similarly, Beaufort et al. (2019) identified the main drivers of intermittence across headwater streams in France using regression models and found high predictive power. In a series of papers, Cheng et al. (2012), Ye et al. (2012), Coopersmith et al. (2012) and Yaeger et al. (2012) related the shape of flow duration curves to regional differences in catchment characteristics. For almost 200 catchments across the contiguous US, the flow duration curves could be regionalized using a set of regression parameters. However, the physical mechanisms and the regional differences affecting these flow duration curves remained largely unknown.

Although most studies agree that streamflow during long dry periods is fed by groundwater (Browne, 1981; Smakhtin, 2001; Fleckenstein et al., 2006), the influence of geology and geomorphology on the magnitude of low-flow metrics or recession characteristics remains often unclear (Barthel, 2014; Bloomfield et al., 2009). Konapala and Mishra (2020) quantified the influence of climate and catchment characteristics on hydrological droughts across the contiguous US and stressed the need for better exploitation of non-climatic characteristics, such as soil properties, geology and land cover, to predict low-flow characteristics. However, Addor et al. (2018) found that the power of non-climatic attributes, such as soil properties, geology and land cover, to predict hydrological signatures was low. They attributed this mainly to the poor representation of such catchment characteristics at the continental scale. Bloomfield et al. (2009) assessed the geologic controls on low flows across a large basin in Great Britain and found that a baseflow index can be predicted by regression approaches, but also pointed out that these regression models can only be applied successfully when including expert judgement and adequate homogenized hydrogeological input information. Gnann et al. (2021) showed that regional knowledge of the geology and weathering characteristics can improve the predictability of low-flow signatures. However, this type of geologic information is often difficult to incorporate in regional or national scale analyses because it is difficult to homogenize the available data on geology or geomorphology to an extent that makes this information comparable across scales. In addition, streamflow during dry periods is often related to very specific geological features that are not mapped at a sufficient resolution (e.g. different lithologies or quaternary deposits). For example, Coehand et al. (2019) and Florianicic et al. (2018) showed that in Alpine catchments distinct geomorphic features and geological layers, such as thick layers of Quaternary deposits or specific bedrock lithologies (i.e. sandstone, gypsum) provided the majority of flow during low-flow periods. Similarly, Naef et al. (2015) showed that sandstone layers in the Swiss Plateau region provide a relatively large portion of the streamflow during low-flow periods. Carlier et al. (2018) then used these findings to determine the importance of sandstone layers for the magnitude of low flows for 21 Swiss catchments.

Such local knowledge or expert judgement of the geological and geomorphic characteristics that are important for low flows can be obtained from spatially distributed streamflow measurements in small catchments (e.g. Fischer et al., 2015; Florianicic et al., 2018; Florianicic et al., 2019; Schneider, 1965; Segura et al., 2019). It is usually assumed that the knowledge gained from these synoptic surveys or snapshot campaigns is transferable to other headwater catchments and possibly larger catchments. However, this is rarely tested because most snapshot campaign studies focus on only one or a few catchments. Florianicic et al. (2019) showed that although the variation in low-flow magnitude within individual headwater catchments was related to catchment characteristics, the relations differed between catchments in the same region.

So far, few studies have compared the catchment characteristics that explain the spatial variability in specific discharge in small headwater catchments with those that explain the low-flow metrics for larger rivers or at the regional (or national) scale. It thus remains unclear if the local-scale predictors of low-flow magnitudes are also important predictors of low-flow metrics at the regional or national scale. If a certain geologic unit is the most important source of stream water during extended dry periods, then the presence of this unit should explain both the intra-catchment variability of low flow at the headwater catchment scale and the inter-catchment variability at the regional scale. Alternatively, it can be argued that specific storage areas or storage features can be the dominant source of stream water locally but that their effect at the regional scale is small due to the
large number of other sources. In addition, the factors that describe the variation in the average response between catchments may not be the same as those that affect the local variation within a catchment at an instant in time. Trends may even become opposite after aggregation, i.e. trends in the behaviour gleaned from mean catchment properties across many catchments may be very different from the trends determined from local variations within a single catchment (cf. Simpson's paradox).

Therefore, in this study we link low-flow metrics from snapshot campaigns at the local headwater scale with low-flow metrics determined at the regional scale from gauging station data. We provide a multi-scale and multi-catchment analysis of the catchment characteristics that can be used to explain or predict the variability in low-flow metrics across Switzerland. In low-elevation catchments in Switzerland, low flows typically occur in summer and autumn; in higher-elevation, Alpine catchments they typically occur in winter (Floriancic et al., 2020; Wehren et al., 2010). Thus, for our analysis, we focused on two regions (see Figure 1): the Swiss Plateau and the Swiss Alps. More specifically, the aim was to answer the following research questions:

1. What are the major catchment characteristics that explain the magnitude of low-flow metrics regionally (i.e. for the Swiss Plateau and Swiss Alps)?
2. How do the catchment characteristics that explain the variation in the magnitude of low flows across small sub-catchments differ from those that explain the average low-flow metrics for larger catchments?

2 | DATA AND METHODS

2.1 | General approach

We compared the catchment characteristics that can explain the spatial variation in low-flow magnitudes at 1) the regional scale and 2) the small headwater scale. For the regional scale analysis, we used gauging station data for 280 gauged catchments across two regions in Switzerland: the Swiss Plateau and the Swiss Alps (Figure 1). We used the streamflow data to calculate three low-flow metrics that are widely used in the literature: 1) the average of the annual 7-day minimum streamflow ($q_{min}$), 2) the average of the streamflow that was reached or exceeded 95% of each year ($q_{95}$), and 3) the master recession constant (C). For each of the catchments, we also determined 44 catchment characteristics based on available national scale geo-data, and developed and tested a random forest regression model to predict the three low-flow metrics in each region.

For the small headwater scale, we used the findings from 16 snapshot field campaigns during low-flow conditions in 2015 and 2016. We identified the catchment characteristics that explain the spatial variability in specific discharge for each catchment during low-flow conditions and compared the results for all catchments in a region. The sub-catchments for which flow was measured during the field campaigns are significantly smaller ($p < 0.001$ Student's t-test) than the catchments of the gauging stations in our regional dataset (median catchment size 2.0 km² for all measurement sites of the snapshot campaigns and 39.1 km² for the gauged catchments; Figure 2).

2.2 | Regional scale analysis

2.2.1 | Streamflow data and low-flow metrics

Daily streamflow data for the period 2000–2018 were collected from the Swiss Federal Office of the Environment (FOEN) and Swiss Cantonal authorities for 380 gauging stations. Across Switzerland, and especially in the densely populated Swiss Plateau region, streamflow is impacted by water abstractions and regulation. To include a large number of catchments in the analyses, which is needed to guarantee the robustness of the regression analysis, we excluded catchments where streamflow was obviously influenced by abstractions (based on an assessment of the meta data for each gauging station and visual

**FIGURE 1** The location of the 280 gauging stations (black dots) and the headwater catchments where we did the field campaigns (coloured basins). The background shading indicates the two study regions: Swiss Plateau (dark red) and Swiss Alps (blue). The area underlain by the karstified Jura limestone (grey) was not included in the analyses.
2.2.2 | Catchment characteristics

The catchment size for each gauging station and the average elevation were determined using a 2 m resolution DEM (SwissAlti3D 2016, Swiss Federal Office of Topography—Swisstopo). We obtained the main catchment characteristics (climate, topography, land cover and geology) for each catchment from available data from the Federal Office of Meteorology and Climatology (MeteoSwiss) and the Federal Office of Topography (Swisstopo; Table 1). Daily gridded datasets of precipitation and air temperature (MeteoSwiss) were used to calculate the spatially averaged mean monthly and annual precipitation (P) and potential evapotranspiration (PET) based on the method of Hargreaves and Samani (1985) for each catchment for the 2000–2018 study period. The average of the mean annual precipitation was 1279 mm (±254 mm, standard deviation) for the 192 Swiss Plateau catchments and 1585 mm (±308 mm) for the 88 Swiss Alpine catchments. The average of the mean annual PET was 742 mm (±57 mm) and 527 mm (±70 mm), respectively.

The 2m resolution DEM was used to calculate several topographic catchment descriptors: upslope area, exposition, slope (average slope, and fraction of area for different slope classes), average terrain roughness (1/cos(β), where β is the pixel slope; Li et al., 2018), average topographic wetness index (TWI; ln(a/tan(β)), where a is the accumulated area for every pixel; Beven & Kirkby, 1979), and the drainage density (Ld/A, where Ld is total channel length derived from the Swiss Vector dataset—Swisstopo, and A is catchment size; Tarboton et al., 1992).

We derived the catchment average storage capacity, permeability and soil depth from the Swiss Soil Map (1:200000—Swisstopo). We used the Swiss Topographic Landscape Model (swissTLM3D—Swisstopo) to determine the percentage of catchment area in one of the four landscape classes: outcrop/bedrock, unconsolidated material, water bodies/wetlands and forests. We used estimates of the depth of unconsolidated material (in three classes) from the “Mächtigkeitsmodell Lockergestein” (Swisstopo). We used the GeoMol dataset for the Swiss Plateau and merged all 222 maps from the GeoCover geology dataset (both from Swisstopo) for all of Switzerland (resolution of 1:25000), homogenized the more than 450 000 feature classes and split the information into two layers: bedrock geology and Quaternary deposits. The bedrock geology layer consists of five different classes: three different sedimentary molasse layers (from GeoMol), sedimentary bedrock, and crystalline bedrock. The Quaternary deposits were grouped into five classes based on their origin: alluvial deposits, glacial deposits, debris deposits, landslides, and all other deposits (e.g., swamps, artificial deposits, etc.).

2.2.3 | Relation of low-flow metrics to catchment characteristics

We assessed the Spearman rank correlation (rS) between the low-flow metrics for the 280 Swiss gauging stations for the two regions Swiss
TABLE 1 Overview of the catchment characteristics, the original dataset and source. The climate data (precipitation and evapotranspiration) were obtained from MeteoSwiss, the catchment characteristics from Swisstopo.

| ID | Type                                | Obtained info and classes          | Abbreviation | Unit | Datasource                                               |
|----|-------------------------------------|------------------------------------|--------------|------|---------------------------------------------------------|
| 1  | Precipitation                       | Annual mean (2000–2018)            | P<sub>mean</sub> | mm   | RhiresD (1 × 2 km) MeteoSwiss                           |
| 2  | Summer mean (May–November)          | P<sub>summer</sub>                 |              |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 3  | Winter mean (December–April)        | P<sub>winter</sub>                 |              |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 4  | Potential evapotranspiration        | Annual mean (2000–2018)            | PET<sub>mean</sub> | mm   | TabsD, TminD, TmaxD (1 × 2 km)—MeteoSwiss              |
| 5  | Summer mean (May–November)          | PET<sub>summer</sub>               |              |      | TabsD, TminD, TmaxD (1 × 2 km)—MeteoSwiss              |
| 6  | Winter mean (December–April)        | PET<sub>winter</sub>               |              |      | TabsD, TminD, TmaxD (1 × 2 km)—MeteoSwiss              |
| 7  | Upslope area                        | Watershed (ArcGIS—spatial analyst) | size         | km<sup>2</sup> | SwissAlt3D 2016 (2 m) Swisstopo                        |
| 8  | Elevation                           | Minimum elevation                  | H<sub>min</sub> | m asl | RhiresD (1 × 2 km) MeteoSwiss                           |
| 9  | Maximum elevation                   | H<sub>max</sub>                    |              |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 10 | Average elevation                   | H<sub>avg</sub>                    |              |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 11 | Total relief (max–min)              | Relief                             |              |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 12 | Slope                               | Average exposition                 | Aspect<sub>xxx</sub> |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 13 | Average slope                       | Slope<sub>avg</sub>                | °             |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 14 | Percent area with slope < 10°       | Slope<sub>10</sub>                 | %             |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 15 | Percent area with slope < 30°       | Slope<sub>30</sub>                 | %             |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 16 | Percent area with slope > 60°       | Slope<sub>60</sub>                 | %             |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 17 | Roughness                           | Roughness (ArcGIS—spatial analyst) | Roughness    | [−]  | RhiresD (1 × 2 km) MeteoSwiss                           |
| 18 | TWI                                 | TWI                                | [−]          | −    | RhiresD (1 × 2 km) MeteoSwiss                           |
| 19 | Drainage density                    | Channel length/upslope area        | Drainage     | km<sup>2</sup> | RhiresD (1 × 2 km) MeteoSwiss                           |
| 20 | Soil parameters                     | Catchment average storage capacity,| Storage<sub>avg</sub> | mm   | RhiresD (1 × 2 km) MeteoSwiss                           |
| 21 | Permeability                        | Permeability<sub>avg</sub>         | cm d<sup>−1</sup> |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 22 | Soil depth                          | Soil depth<sub>avg</sub>           | cm            |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 23 | Land cover                          | Outcrop/bedrock                    | Bedrock      | % Area | RhiresD (1 × 2 km) MeteoSwiss                           |
| 24 | Unconsolidated material             | Unconsolidated material            | Debris       | % Area | RhiresD (1 × 2 km) MeteoSwiss                           |
| 25 | Water bodies, swamps                | Water bodies, swamps               | Waters       | % Area | RhiresD (1 × 2 km) MeteoSwiss                           |
| 26 | Forest                              | Forest                             | Forests      | % Area | RhiresD (1 × 2 km) MeteoSwiss                           |
| 27 | Depth of unconsolidated material    | 0 m                                | Depth<sub>0</sub> | % Area | RhiresD (1 × 2 km) MeteoSwiss                           |
| 28 | 0.1–10 m                            | Depth<sub>0.1–10</sub>             | % Area        |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 29 | >10 m                               | Depth<sub>0.1–10</sub>             | % Area        |      | RhiresD (1 × 2 km) MeteoSwiss                           |
| 30 | Geology                             | Upper freshwater molasse            | OSM          | % Area | GeoCover (1:25.000) & GeoMol                           |
| 31 | Upper marine molasse                 | OMM                                 | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 32 | Lower freshwater molasse             | USM                                 | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 33 | Alpine crystalline rocks            | Crystalline                         | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 34 | Alpine sedimentary rocks            | Sedimentary                         | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 35 | Quaternary deposits                 | Alluvial deposits                   | Alluvial      | % Area | GeoCover (1:25.000) & GeoMol                           |
| 36 | Glacial deposits                    | Glacial                             | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 37 | Debris deposits                     | Debris                              | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 38 | Landslides                          | Landslide                           | % Area        |      | GeoCover (1:25.000) & GeoMol                           |
| 39 | Other                               | Other                               | % Area        |      | GeoCover (1:25.000) & GeoMol                           |

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Plateau and Swiss Alps and the 44 catchment characteristics. We also used the $r_S$ to determine the correlation between the discharge measurements during low-flow in the Swiss headwater catchments and the 44 catchment characteristics. To explore which of the 44 catchment descriptors were most strongly related to the low-flow metrics, we used the random forest relative importance algorithm. Random forests allow assessment of the relative importance of the catchment characteristics to explain the observed variation (for more information, see Breiman, 2001 and Cutler et al., 2007). They are based on an ensemble of decision trees to assess the predictive power of the variable input characteristics, and are known to be relatively insensitive to the effects of collinearity. The method has previously been used to find suitable explanatory variables for hydrological prediction (e.g. Booker & Snelder, 2012; Prieto et al., 2019; Zhang et al., 2018) and to relate streamflow signatures to catchment characteristics (e.g. Addor et al., 2018; Konapala & Mishra, 2020; Snelder et al., 2013).

We created separate random forest models for the two regions for each of the three low-flow metrics ($q_{q_{\text{min}}}$, $q_{95}$ and $C$) using the full dataset of catchment characteristics ($n = 44$). Prior transformation of the low-flow metrics (root square and log) did not increase the overall performance of the regression approaches, therefore we present the results for the untransformed data throughout the manuscript. The possible predictors were computed by 10-fold cross-validation, each creating an ensemble of 1000 regression trees using non-transformed response variables. We considered the 11 catchment characteristics with the highest relative importance (i.e. the top 25% catchment characteristics), based on the decrease in Gini impurity (the measure of probability of miss-classification). We then used these 11 catchment characteristics and the random forest models to predict the three low-flow metrics ($q_{q_{\text{min}}}$, $q_{95}$ and $C$) for the two regions (Swiss Plateau and Swiss Alps). The analyses were completed using the MATLAB “Regression Tree Ensembles” functions (v2018b).

2.3 | Headwater catchment scale

2.3.1 | Field campaigns

We conducted field campaigns during the summer and autumn of 2015 in nine catchments on the Swiss Plateau (red shading in Figure 1). In addition, we used the data from snapshot campaigns in seven Alpine catchments in winter 2016 from Floriancic et al. (2019). In each catchment, we conducted a 1-day snapshot campaign to measure streamflow at 2–39 (average: 12) sites across each catchment (Table 2). Where possible, we measured the streamflow directly with a bucket and stopwatch (Table 2—numbers in parentheses). At all other places, we measured streamflow using the salt dilution method, following the methodology of Moore (Moore, 2004; Moore, 2005), see Floriancic et al. (2018) for the measurement protocol. We divided the measured streamflow by the accumulated area at each measurement point to obtain the specific discharge ($q$).

The locations of the measurements were based on a preliminary GIS analysis of the topography and the stream network, to ensure that we capture all tributaries and potential low-flow sources. The timing of the snapshot campaigns was based on data from a gauging station at the outlet of the catchment or a neighbouring catchment. The streamflow at the outlet was less than the 75th percentile ($q_{95}$; Table 2) during all snapshot campaigns, indicating that all campaigns were conducted during a low-flow period.

2.3.2 | Relations between landscape characteristics and specific discharge

For each of the 215 measurement points in the 16 headwater catchments, we calculated the area draining to that point, and determined the same landscape characteristics as for the regional scale data analysis (see Section 2.1; Table 1) for this drainage area. We calculated the $r_S$ correlation to determine the relation between the specific discharge and the catchment characteristics for each of the 16 catchments and for all points on either the Swiss Plateau or in the Swiss Alps. This allowed us to assess differences between catchments in the same region, as well as differences between the two regions. Although the measurements in the different catchments were carried out on different days, the measurements are comparable because they all took place at a comparable small discharge (i.e. less than the 75th percentile—Table 2). Again, we also used the random forest relative importance algorithm to assess the 11 most important explanatory variables for each of the two regions.

3 | RESULTS

3.1 | Low-flow metrics across Switzerland

3.1.1 | Spatial variability in low-flow metrics

The average low-flow magnitude was significantly lower for the gauged catchments on the Swiss Plateau than in the Swiss Alps (average $q_{\text{min}} = 0.38 \text{ mm day}^{-1}$ vs. $0.62 \text{ mm day}^{-1}$ and average $q_{95} = 0.45 \text{ mm day}^{-1}$ vs. $0.72 \text{ mm day}^{-1}; p < 0.001$; see Table 3 for median values). However, within each region the low-flow magnitudes were highly variable (Figure 3), as also reflected by the coefficient of variation ($CV > 0.5$; Table 3). The average master recession constants were somewhat smaller for the streams on the Swiss Plateau than in the Swiss Alps (average: 14.6 days versus 16.8 days; $p < 0.001$) and were regionally slightly more consistent than $q_{\text{min}}$ and $q_{95}$ ($CV = 0.5$; Table 3). The master recession constant ($C$) was only weakly correlated with $q_{\text{min}}$ or $q_{95}$ (e.g. $r_S$ for the relation with $q_{\text{min}}$ of 0.42 for the Swiss Plateau catchments and 0.10 for the Swiss Alps). Across the two Swiss regions the three low-flow metrics varied more than the climate variables (e.g. CV of mean annual precipitation is $\approx 0.2$ for the
Swiss Plateau and the Swiss Alps catchments), and were also much more variable over short distances (see Figure S1). This suggests that the variation of low-flow metrics across a region is more strongly affected by the variation in catchment characteristics than the variation in climate characteristics (e.g. precipitation, evapotranspiration, snow storage).

### TABLE 2
Information on the field campaigns in the headwater catchments: Name and ID of the stream, catchment area, number of streamflow measurements (number of bucket measurements in parentheses), specific discharge at the outlet $q$, the flow percentile at the time of the measurements based on the data for the gauging station at the outlet or a neighboring stream, mean annual precipitation ($P$) and mean annual potential evapotranspiration ($\text{PET}$) from the Rhires dataset of Swisstopo.

| Name          | ID | Date       | Catchment area | Number of measurements | $q$ at outlet | Flow percentile | Mean annual $P$ | Mean annual $\text{PET}$ |
|---------------|----|------------|----------------|------------------------|---------------|-----------------|----------------|--------------------------|
| Swiss Plateau |    |            |                |                        |               |                 |                |                          |
| Gruene        | P1 | 9/2/15     | 80.7           | 39 (16)                | 0.18          | 96$^a$          | 1260           | 780                      |
| Jona          | P2 | 8/13/15    | 24.8           | 6                      | 0.37          | 98              | 1490           | 730                      |
| Langete       | P3 | 8/20/15    | 95.0           | 23                     | 0.76          | 81              | 1250           | 780                      |
| Muehlibach    | P4 | 7/17/15    | 31.6           | 13                     | 0.44          | 91$^a$          | 1140           | 740                      |
| Naefbach      | P5 | 7/7/15     | 36.4           | 9                      | 0.42          | 84              | 1050           | 810                      |
| Oenz          | P6 | 9/11/15    | 85.5           | 8                      | 0.55          | 94              | 1150           | 800                      |
| Rot           | P7 | 9/12/15    | 56.4           | 8 (2)                  | 0.31          | 98              | 1150           | 790                      |
| Toess         | P8 | 8/31/15    | 11.3           | 8 (3)                  | 0.17          | 98              | 1770           | 630                      |
| Uerke         | P9 | 7/14/15    | 25.0           | 19 (4)                 | 1.02          | 90              | 1090           | 780                      |
| Swiss Alpine  |    |            |                |                        |               |                 |                |                          |
| Berninabach   | A1 | 3/12/16    | 109.1          | 5                      | 0.24          | 94              | 1300           | 430                      |
| Dischmabach   | A2 | 2/7/16     | 43.3           | 10                     | 0.75          | 86              | 1250           | 470                      |
| Goneri        | A3 | 1/30/16    | 39.9           | 7                      | 0.86          | 94              | 1850           | 450                      |
| Krummbach     | A4 | 2/20/16    | 19.5           | 9                      | 0.62          | 95              | 1670           | 500                      |
| Ova dal Fuorn | A5 | 3/10/16    | 55.2           | 13                     | 0.67          | 84              | 1080           | 580                      |
| Poschiavino   | A6 | 3/11/16    | 14.4           | 11                     | 0.83          | 96              | 1540           | 510                      |
| Rosegbach     | A7 | 3/12/16    | 65.5           | 2                      | 0.29          | 78              | 1250           | 420                      |

$^a$Note that the flow percentiles for P1 and P4 were based on data from a neighboring gauged catchment.

### TABLE 3
Descriptive statistics (average, median, range, standard deviation, coefficient of variation, skewness) for the mean of the annual 7-day minimum flow ($q_{\text{min}}$ in mm day$^{-1}$), the mean streamflow that was reached or exceeded for 75 or 95% of the days during each year ($q_{75}$ and $q_{95}$ in mm day$^{-1}$), and the master recession constant ($C$ in days) for the catchments on the Swiss Plateau and Swiss Alps. Student $t$-tests showed that the average values for the Swiss plateau and Swiss Alpine catchments were statistically different for all low-flow metrics ($p < 0.01$).

|                     | Swiss Plateau ($n = 192$) | Swiss Alps ($n = 88$) |
|---------------------|---------------------------|------------------------|
| $q_{\text{min}}$   | 0.38                      | 0.62                   |
| $q_{75}$           | 0.71                      | 1.12                   |
| $q_{95}$           | 0.45                      | 1.24                   |
| $C$                | 14.60                     | 6.22                   |
| Average            |                           |                        |
| Median             | 0.33                      | 0.62                   |
| Range (max minus min) | 1.23                    | 2.00                   |
| Standard deviation | 0.25                      | 0.47                   |
| Coefficient of variation | 0.67                  | 0.66                   |
| Skewness           | 0.88                      | 1.39                   |

### 3.1.2 Explanatory power of the catchment characteristics for the low-flow metrics

#### Random forest relative importance

All three low-flow metrics were related to climate variables to some extent, but also to geology, topography and forest cover. The
catchment characteristics that could describe the variability in the magnitude of $q_{\text{min}}$ and $q_{95}$ differed from those that were able to describe the variability in the recession constant ($C$) (Figure 4).

For the Swiss Plateau, the spatial variation of low-flow magnitude ($q_{\text{min}}$ and $q_{95}$) can be explained by catchment topography (slope$_{\text{avg}}$, percentage area with slope$_{10}$, slope$_{60}$, and roughness). The percentage of area underlain by sandstones of the upper marine molasse (OMM) and covered by alluvial deposits.

The variation in $q_{\text{min}}$ and $q_{95}$ for the catchments in the Swiss Alps can be explained by topography (slope$_{\text{avg}}$, percentage area with slope$_{10}$, slope$_{60}$, and roughness). The elevation ($H_{\text{avg}}, H_{\text{min}}$), the percentage of area covered by forests, and the area underlain by crystalline rocks were good descriptors as well. The recession constant $C$ was also related to elevation and percentage of area covered by forests, but even more closely related to the total area covered by Quaternary deposits (Figure 4).

Correlation analysis

There was a slight positive correlation between catchment size and the magnitude of $q_{\text{min}}$ and $q_{95}$ for both the Swiss Plateau catchments (Figure 5a) and the Swiss Alpine catchments (Figure 5k and Figure S2). Swiss Plateau catchments with a larger percentage of area with a slope between 10° and 30° had a higher $q_{\text{min}}$ and $q_{95}$ (Figure 5b), but for the Swiss Alpine catchments this relation was negative (Figure 5m). In general, Alpine catchments with steeper slopes had a higher $q_{\text{min}}$ and $q_{95}$ but the correlations between average slope (Figure 5l), the area with a slope between 30° and 60°, or a slope <10° (Table 4) and the low-flow metrics were not statistically significant. Swiss Plateau catchments with a higher drainage density had lower low flows (Figure 5c) but the correlation was weak for Swiss Alps (Table 4). The $q_{\text{min}}$ and $q_{95}$ were also higher for Swiss Plateau catchments with a relatively large area underlain by sandstones of the upper marine molasse (OMM) (Figure 5d) and catchments covered by alluvial deposits (Figure 5e).

3.1.3 | Predictive regression model

We predicted the low-flow magnitudes ($q_{\text{min}}$ and $q_{95}$) and the recession constant ($C$) using the random forest regression model with the 11 best predictors (i.e. the characteristics with highest relative importance, see Figure 4 and Section 3.1.2). In general, the random forest model tended to overestimate the lowest $q_{\text{min}}$ and $q_{95}$ values and underestimate the highest values, resulting in a lower simulated variation in $q_{\text{min}}$ and $q_{95}$ than observed (Figure 6). The random forest predicted the low-flow metrics better for the Swiss Plateau catchments than the Swiss Alpine catchments (higher $R^2$ and lower RMSE—Figure 6). Across the Swiss plateau, the low-flow metrics could be predicted with an error smaller than 30% for approximately 80% of the catchments ($q_{\text{min}}$: 71%, $q_{95}$: 78%, and $C$: 92%); for the Swiss Alps this was only the case for approximately 60% of the catchments ($q_{\text{min}}$: 64%, $q_{95}$: 56%, and $C$: 64%). For fewer than 7% of the catchments on the Swiss Plateau and 20% of the catchments in the Swiss Alps the errors were larger than 50%.

The residuals (i.e. the differences between the predictions and the observations) were spatially variable even over short distances (Figure 7). For $q_{\text{min}}$ and $q_{95}$, the residuals were especially high in the northwest and the eastern part of Switzerland. For the Alpine catchments, model prediction errors were larger in the south-western and
central parts of the Alps. The high variability in the residuals reflects the high variability in the magnitude of low flows (Figure 3) and suggests that this variability cannot fully be explained by the selected catchment attributes.

3.2 Variability in specific discharge across headwater catchments

The specific discharge during the snapshot campaigns in the headwater catchments varied from 0.17 to 1.02 mm day$^{-1}$ for the Swiss Plateau catchments and between 0.24 and 0.86 mm day$^{-1}$ for the Swiss Alpine catchments. Specific discharge was highly variable for most of the 16 studied catchments (Figure 8, see Figure S4 for the maps). The coefficient of variation of specific discharge within a single headwater catchment varied between 0.17 and 0.96 (median: 0.40) for the Swiss Plateau catchments and between 0.14 and 0.43 (median: 0.28) for the Swiss Alpine catchments (Table 5).

As previously observed by Naef et al. (2015), specific discharge ($q$) in catchments on the Swiss Plateau was higher for sub-catchments with sandstone layers of the upper marine Molasse (blue areas in the background of Figure 9a). For almost all the sub-catchments in the sandstone area, specific discharge was higher than 0.6 mm day$^{-1}$, whereas for the other catchments, specific discharge was less than 0.6 mm day$^{-1}$. For some catchments, we found noticeable differences in specific discharge between upstream river reaches (or headwater areas) and reaches further downstream. For others, we found large differences in specific discharge along the river reach (Figure 9b), suggesting the presence of losing and gaining sections or flow through the streambed or hyporheic zone. In several sub-catchments, especially in the Swiss Alps, deeply incised rivers (with steep slopes close to the river) tended to have a higher specific discharge than reaches that drained sub-catchments where the steep slopes were located further away from the river (see Figure 9c).

4 DISCUSSION

4.1 Relevant catchment characteristics for low-flow assessment and prediction

The field campaigns and large-scale data evaluation both provided insights into the catchment characteristics that can be used to predict low-flow magnitudes. Topography often reflects geology and also influences the hydraulic gradient and thus groundwater flow to the stream. Low-flow magnitudes (e.g. Cervi et al., 2017; Li et al., 2018) and hydrograph recession rates (e.g. Bloomfield et al., 2009; Bogaart et al., 2016; Karlsen, Grabs, et al., 2016; Krakauer & Temimi, 2011; Mutzner et al., 2013) have previously been related to topography. Li et al. (2018) reported that topographic indices (e.g. surface area, perimeter, slope length factor) can be used to predict low-flow magnitudes in snow-dominated catchments. Mutzner et al. (2013) showed for a dataset of 27 Swiss catchments that the variation in low-flow magnitude can be predicted based on data that can be derived from...
the DEM (e.g. channel network characteristics). Indeed, catchment average elevation and slope were correlated to the low-flow metrics ($q_{min}$, $q_{95}$ and $C$) (Figures 4, 5; Table 4), as reported also in previous studies (e.g. Kroll et al., 2004; Li et al., 2018; Staudinger et al., 2015).

The effect of elevation was already reported in previous studies but there is on-going discussion about the reasons for this difference. For example, Staudinger et al. (2017) and Jasechko et al. (2016) argued that the storage potential increases with relief and the higher relief in

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**FIGURE 5** The Spearman rank correlation between the most relevant catchment characteristics (i.e. highest relative importance, see Figure 4) and $q_{min}$ for all gauging stations (upper panels: a–e and k–o) and the specific discharge ($q$) measured at all sub-catchments during field campaigns in the headwater catchments (lower panels: f–j and p–t) for the catchments on the Swiss Plateau (red outlined box a–j) and in the Swiss Alps (blue outlined box, k–t). The straight lines for the results of the field campaigns (lower panels: f–j and p–t) represent the linear regression lines for each individual headwater catchment. The Spearman rank correlation coefficients are printed in black bold font when the correlations for all data points were significant ($p < 0.05$) and in grey if they were not significant ($p > 0.05$). The correlations between these catchment characteristics and $q_{95}$ and $C$ were similarly poor and variable and are shown in Figures S2 and S3.
TABLE 4  The spearman rank correlation between catchment characteristics and mean $d_{min}$ (mm day$^{-1}$) for the 2000–2018 study period at the 280 gauging stations, as well as the specific discharge $q$ (mm day$^{-1}$) measured during the field campaigns in 2015 and 2016 for the catchments on the Swiss Plateau and in the Swiss Alps.

| Topography | Swiss Plateau | Swiss Alps | Swiss Plateau | Swiss Alps |
|------------|---------------|------------|---------------|------------|
| Size       | $q_{min}$     | $q_{95}$   | $q$           | $q_{min}$  |
| $H_{min}$  | 0.36          | 0.13       | -0.54         | Bedrock    |
| $H_{max}$  | 0.08          | -0.49      | -0.13         | -0.07      |
| $H_{avg}$  | 0.29          | -0.46      | 0.14          | -0.36      |
| Relief     | 0.46          | 0.24       | -0.26         | 0.24       |
| Slope$_{avg}$ | 0.44      | 0.07       | 0.20          | Depth$_{0}$ |
| Slope$_{<10^\circ}$ | -0.46 | 0.14 | -0.33 | Depth$_{10}$ |
| Slope$_{10^\circ–30^\circ}$ | 0.49 | 0.26 | -0.05 | -0.20 |
| Slope$_{30^\circ–60^\circ}$ | 0.44 | -0.46 | -0.02 | 0.22 |
| Slope$_{>60^\circ}$ | 0.40 | -0.48 | 0.16 | -0.21 |
| Roughness  | 0.44          | -0.09      | 0.14          | 0.05       |
| TWI        | 0.15          | 0.17       | 0.11          | -0.20      |
| Indices    |               |            |               |            |
| Drainage density | -0.21 | -0.43 | -0.05 | 0.07 |
| Storage$_{avg}$ | -0.36 | NA | 0.02 | NA |
| Permeability$_{avg}$ | -0.11 | NA | -0.12 | NA |
| Soil depth$_{avg}$ | -0.26 | NA | 0.02 | NA |
| Soils      |               |            |               |            |
| Bedrock    | 0.39          | -0.27      | 0.14          | -0.12      |
| Debris     | 0.32          | -0.19      | -0.05         | -0.17      |
| Waters     | 0.18          | -0.14      | 0.15          | -0.44      |
| Forest     | 0.21          | -0.10      | -0.04         | 0.30       |
| Depth$_{0}$ | 0.24          | -0.24      | -0.17         | 0.35       |
| Depth$_{1–10m}$ | -0.21 | 0.32 | 0.12s | -0.21 |
| Depth$_{10m}$ | -0.17 | 0.11 | 0.24 | -0.04 |
| Geology    |               |            |               |            |
| Quaternary |               |            |               |            |
| Crystalline |               | NA | NA | -06.06 |
| Sedimentary |               | NA | NA | -0.04 |
| Total      | -0.22         | 0.34       | 0.00          | 0.14       |
| Alluvial   | 0.25          | 0.25       | 0.02          | -0.15      |
| Glacial    | -0.30         | 0.26       | 0.02          | 0.15       |
| Debris     | 0.23          | 0.09       | -0.14         | -0.22      |
| Landslide  | 0.17          | 0.09       | 0.16          | 0.04       |

Note: The colours indicate the direction of the relation (orange indicates a negative correlation, green a positive correlation), darker colours indicate a significant correlation ($p < 0.05$), and all non-significant results ($p > 0.05$) are indicated by a light background colour. NA and grey background indicate an impossible combination or a lack of data. See Table 1 for the abbreviations of the catchment characteristics. For the correlations with $q_{95}$ and C, see Table S2.

FIGURE 6  Comparison of the observed and predicted values for $q_{min}$ and $q_{95}$ (both in mm d$^{-1}$) and the recession constant C (in days) for the catchments on the Swiss Plateau (red) and the Swiss Alps (blue). The predicted values are based on the random forest regression model with the 11 best (top quartile) predictors (see Table S1 for the list).

mountainous catchments increases the connectivity of the storage areas to the river network. In addition, mountain regions are more fractured because of tectonic stress during uplift (Molnar et al., 2007), which may increase their storage potential. Catchments at higher elevations (in Switzerland) also receive more precipitation, and potential evapotranspiration is lower. The median annual precipitation is 1200 mm (inter quartile range: 301 mm) for the Swiss Plateau and 1610 mm (inter quartile range: 409 mm) for the Swiss Alpine catchments, respectively. The median annual potential evapotranspiration is 760 mm (inter quartile range: 61 mm) and 520 mm (inter quartile range: 100 mm), respectively. Evapotranspiration impacts low flows that occur in summer and fall in the Swiss Plateau catchments (Figure 4), but is less likely to affect the low flows in the Swiss Alps that occur during the cold season. The impact of evapotranspiration on low flows has been analysed in previous studies (i.e. Federer, 1973; Floriancic et al., 2020; Karlsen et al., 2019; Tashie et al., 2020), however the small inter-catchment variabilities of evapotranspiration cannot explain the variability of low-flow metrics across the two Swiss regions (Plateau and Alps) i.e. coefficient of variation of mean annual potential evapotranspiration and $q_{min}$ of 0.2 versus 0.6 and 0.2 versus 0.5 for the Swiss Plateau and Swiss Alps, respectively.

The effect of slope differed for the two regions. For the Swiss Plateau, the steeper catchments generally had lower low flows, whereas in the Swiss Alps, catchments with steeper slopes (above 30$^\circ$) tended to have higher low flows. The contradictory results for catchments of the two Swiss regions could be related to the
The spatial distribution of the residual errors for the predicted low-flow metrics $q_{\text{min}}$, $q_{95}$ and C, expressed in % (100% $\times$ (predicted-observed)/observed). The maps show that there is a distinct spatial variation in the accuracy of the random forest models, as well as a high variability in the residuals for nearby gauging stations. 

The measurements during the field campaigns suggest that the total area covered by Quaternary deposits has a positive effect on low flows as well. Unconsolidated materials can store large amounts of water and also favour percolation to deeper groundwater aquifers (e.g. Coehand et al., 2019; Floriancic et al., 2018; Langston et al., 2011; Roy & Hayashi, 2009; Winkler et al., 2016). Furthermore, our results suggest that soil physical characteristics (storage capacity, permeability and soil depth) are not particularly informative for regionalization of low-flow characteristics, neither for the gauging station data nor the field campaigns (Figures 4, 5; Table 4). This is not surprising as the hydraulic conductivity of the top soil layers is very low after extended dry periods and drainage from these layers is thus unlikely to contribute to streamflow during the driest periods of the year.

A larger forested area had a positive effect on the low-flow magnitude for the catchments on the Swiss Plateau (both the gauged catchments and the headwater catchments); however, there was a slightly negative effect for the gauged Swiss Alpine catchments. Generally, forests are characterized by high transpiration and interception losses and therefore one can expect the low flows to be smaller for the forested catchments. The effect of evapotranspiration is larger for the warm-season low flows (i.e. the Swiss Plateau) than the cold-season low flows (i.e. in the Swiss Alps, for example, Mastrotheodoros et al., 2020). An explanation for higher low flows in areas with more forests for the higher elevation catchments can be that forests only...
develop where there is sufficient material on top of bedrock (i.e. soil, debris, regolith). Thus, the forest cover may reflect the presence of soil, debris and regolith and water storage in these areas (i.e. the $r_5$ for the correlation between fraction of forest cover and average soil depth was 0.59 for the gauged catchments in the Swiss Alps).

### 4.2 Usefulness of information from small-scale field studies for larger scale predictions

Detailed small-scale field investigations are often assumed to be informative for understanding larger-scale patterns and processes as well. However, findings from one catchment may not be transferable to another catchment and scaling issues may further hinder this transfer of knowledge. During the field campaigns, we found that there are distinct landscape features that affect the magnitude of low flows within specific headwater catchments, but these relations often did not hold for other (or even neighbouring) catchments (see the different directions of the lines in Figures 5 and S2 and also the results of Florianić et al., 2019). Only few correlations were similar for both, the headwater catchments and the gauged rivers, but these tended to also be the strongest correlations, suggesting they are robust and transferable. For example, for the Swiss Plateau catchments, the percent area of molasse sandstones (OMM – Table 4) and percent area with a slope between 10° and 30° (slope10–30°, Table 4) were good predictors for the specific discharge during both the snapshot field campaigns and $q_{\text{min}}$ and $q_{95}$ at the gauging stations. Both datasets also show that a higher drainage density tends to be related to lower low-flow magnitudes.

However, we also found several opposite correlations between catchment characteristics and specific discharge during the field campaigns and the low-flow metrics for the gauging stations (Table 4). This is perhaps not surprising due to the difference in the size of the catchments (Figure 2), as the effects of the small-scale landscape features that are important at the sub-catchment scale are filtered out at the larger scale. However, in part it also reflects that some of the processes involved in low-flow formation are local and highly variable in space. This large spatial variability is reflected in the high spatial variation of the low-flow metrics and the large differences between nearby catchments (Figure 3), as well as in the large variability in residuals of the regression model (Figure 7). Also, the catchment characteristics that describe the differences in the mean response between catchments at the regional scale (i.e. the low-flow metrics: $q_{\text{min}}$ and $q_{95}$) and the characteristics that describe local within-catchment variation at an instant in time (i.e. the specific discharge during the snapshot campaigns) may differ due to the effects of flow aggregation. The correlation between specific discharge in the headwater catchments and sub-catchment characteristics represents a process-based continuity of flow at the sub-catchment scale, whereas at the regional scale the correlations between mean low-flow metrics and catchment characteristics represent a mean catchment response. There is no reason that the magnitude or even the direction of both local and regional correlations to the same catchment characteristics has to be the same (cf. Simpson’s paradox), but the results of this study show that for the most influential catchment characteristics, they are. Thus, detailed field studies can help to assess the small-scale variation in low-flow magnitudes and improve our process understanding, even if results are not statistically significant when looking at a small number of catchments (e.g. some results for the Swiss Alpine catchments, like slope angle or area covered with debris). However, results from one catchment should not be blindly applied to other catchments or larger scales as the relations may be very different and even opposite.

### 4.3 The need for more detailed catchment descriptors

The results of this study show the importance of local characteristics to predict low-flow metrics. However, these features are not easily captured by catchment average values (Karlsen, Seibert, et al., 2016).
The observation that specific discharge was higher for (sub-)catchments with steep slopes near the stream network than further away, for example, highlights the importance of the location of steep slopes, rather than the percentage of the area with steep slopes. Similarly, the location of the storage areas relative to the stream network is likely more important than the fraction of catchment area covered by these storages. Therefore, future studies will likely benefit from the mapping of these specific landscape or catchment characteristics. Field measurements of specific discharge in multiple catchments of a region can highlight which catchment characteristics are useful for prediction.

Currently, most of the non-climatic catchment characteristics that may be useful to predict the magnitude of low flows (e.g., geology, soils and Quaternary deposits) are not mapped in enough detail to be useful for larger scale predictions (e.g., Addor et al., 2018; Bloomfield et al., 2021). For example, only considering Molasse layers would not have led to any significant results, as specific discharge was small in areas of the conglomerate layers of the lower freshwater molasses, but \( q_{\min} \) was high for catchments underlain by the sandstone layers from the Upper Marine Molasse. For most regions such detailed information on specific landscape elements is currently not available, which makes it difficult to use this type of information to predict low-flow metrics across larger scales (Gnann et al., 2021). If field studies in multiple catchments in a region show that characteristics like sandstone layers are important for low flow, then targeted mapping of these features (or homogenization of these features in existing data) may help the development of databases to improve the prediction of low-flow metrics.

Another important step forward could be the analysis of a combination of several catchment characteristics together. For example, our field campaigns (and previous work: Floriancic et al., 2018) revealed that areas covered by quaternary deposits contribute to low flows, but the correlations between the area covered by quaternary deposits and either \( q_{\min} \) or the specific discharge during the field campaigns were rather low (\( r_s > 0.14 \); Figure 4 and Table 4). One reason for these low correlations could be that areas with debris cover will only be able to sufficiently contribute to low flows if they are i) thick enough to store a decent amount of water, ii) steep enough to drain, and iii) well connected to the river network during dry periods. To better use all the (often qualitative) information from field campaigns and previous works, we need to prepare more targeted input datasets, for example by specifically merging different combinations of catchment characteristics (i.e., steep slope close to the channel).

### 4.4 Predictability of low-flow metrics across Switzerland

The random forest regression-based model was able to predict \( q_{\min} \), \( q_{95} \), and \( C \) for many catchments (Figure 6) with an error of less than 30% (approximately 80% of the Swiss Plateau catchments and 60% of the Swiss Alpine catchments). For, less than 7% of the catchments on the Swiss Plateau and 20% of the catchments in the Swiss Alps the errors were greater than 50%. However, there was significant regional and site-to-site variability in the predictability of the low-flow metrics. In addition, the predicted variability in the low-flow metrics was smaller than the observed (Figures 6, 7). Thus, for certain regions (or catchments) the current framework may be useful to predict the low-flow metrics, but in other regions (or catchments) low flows are influenced by catchment characteristics that were not captured by the statistical model and the current catchment descriptors (e.g., for the south-western part of Switzerland; see Figure 7).

The reliability and robustness of the regression approach largely depends on the quality of the input data and we acknowledge that there is uncertainty in both the streamflow data used to calculate the low-flow metrics and the data used to characterize the catchments. Part of the local variation in the residuals is certainly caused by inaccuracies in the explanatory variables (particularly the geological...
descriptors), measurement errors for low flows, and human impacts on the streamflow regimes. If we assume that the measurement errors or human impacts are not spatially organized, then the regional patterns in the residual errors of the regression model (Figure 7) suggest that there are regional differences in the robustness of the model, and thus in the predictability of low-flow metrics. The predictability of the model could be increased if models are developed for smaller regional clusters (other than Plateau and Alps), either based on expert knowledge or detailed findings from further field investigations. Then the models can be trained with a pre-selected, region-specific set of input variables. However, regression techniques, like random forest, are most reliable (and robust) when used with large input datasets. Our sample size of 44 input variables for 192 Swiss Plateau catchments and 88 Swiss Alpine catchments is already critically small, and further subdivisions are not possible.

In addition to the regional differences in the residuals, there were also very large differences in the residuals for nearby locations. This partly reflects the large variation in the low-flow metrics, which were very different for nearby catchments (Figure 3) and may be due to errors in the data or human impacts on the streamflow regime. However, the smaller range for the predicted low-flow metrics than for the observed (Figure 6) also suggests that most likely the characteristics that affect low flows were not well captured in our set of input variables. The large variation in the low-flow metrics is also highlighted by the high variability in specific discharge during the field campaigns (Figure 8), which also suggests that variability in low-flow magnitudes is highly affected by local specifics, which are not captured in the input data.

5 | CONCLUSIONS

We investigated which catchment characteristics are useful to explain the variability in low-flow metrics at the regional scale for 280 gauged catchments across Switzerland and at the small headwater catchment scale for discharge measurements from 16 field campaigns during low-flow periods. The mean annual 7-day minimum flow \( q_{\text{min}} \), the mean streamflow that was reached or exceeded 95% of the days during each year \( q_{95} \), and the master recession constant \( C \) were all highly variable across Switzerland. The snapshot field campaigns in summer 2015 and winter 2016 showed that low-flow magnitudes were also highly variable within headwater catchments.

At the regional scale, we assessed the relation between the low-flow metrics and 44 catchment-averaged characteristics using random forest regression. These results show that \( q_{\text{min}} \) and \( q_{95} \) were higher for Swiss Plateau catchments with a larger percentage area underlain by sandstones of the upper marine molasse, a larger percentage area with slopes between 10° and 30°, or more alluvial deposits. They were smaller for catchments with a high drainage density and a large percentage area covered by conglomerates of the upper freshwater molasse. The low-flow magnitudes in the Swiss Alpine catchments were positively related to the average catchment slope, the area covered by glacial deposits and negatively correlated to the percentage area with a slope less than 10°. These catchment characteristics were also correlated to the specific discharge observed during the snapshot campaigns in the small headwater catchments. For many other catchment characteristics, the correlations differed for the individual headwater catchments, as well as between the small and large catchments. The random forest model, furthermore, showed that the top 25% of catchment characteristics can predict the average low-flow metrics \( q_{\text{min}}, q_{95} \) and \( C \) within a 30% error for eight out of 10 catchments on the Swiss Plateau and six out of 10 catchments in the Swiss Alps, respectively. However, the predicted variation in the low-flow metrics was smaller than observed. The residuals were also larger for the Alpine catchments, suggesting that our current set of input variables does not completely capture low-flow generation across the Swiss Alps as well as for the Swiss Plateau. In general, the spatial organization of residuals suggests that certain regional characteristics are not well covered by the catchment characteristics that were used in this study. However, our results highlight the promising path of combining local sub-catchment information from field studies within regional scale low-flow studies to improve the prediction of low-flow metrics.

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**DATA AVAILABILITY STATEMENT**

The data from the field campaigns across Swiss headwaters can be accessed at https://doi.org/10.3929/ethz-b-000377748. All other data that support the findings of this study are available from the corresponding author upon reasonable request.

**NOMENCLATURE**

- \( C \) master recession constant (calculated according to equation \( Q_l = Q_o \exp(-kt) \) in day\(^{-1}\))
- \( P \) annual average precipitation in mm year\(^{-1}\)
- \( PET \) annual average potential evapotranspiration in mm year\(^{-1}\)
- \( q \) specific discharge measured during the field campaigns in mm day\(^{-1}\)
- \( q_{95} \) average streamflow that is reached or exceeded for 95% of the days in a year in mm day\(^{-1}\)
- \( q_{\text{min}} \) average annual 7-day minimum streamflow in mm day\(^{-1}\)
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