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Reconstructing Flow Dynamics of Temporary Streams Using Citizen Science Data and a Hierarchical Network Structure

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Abstract. Temporary (i.e., non-perennial) streams form a large fraction of the global stream network and are important habitats. However, they are generally excluded from official monitoring networks. Visual observations by citizen scientists provide a valuable opportunity to collect temporary stream data, but these observations are irregular in space and time. We used observations by citizen scientists to derive the hierarchical structure (i.e., fixed order) of stream wetting and drying for a forested hill in Zurich, Switzerland. The dataset consists of 2 to 235 (median: 64) observations for 55 sites, and at least one observation for 402 days over the three-year period. In addition, an expert determined the stream state for 59 sites on 24 days during a six-month period. The hierarchical structure was more uncertain for the citizen science dataset than for the expert data, likely due to the irregularity of the observations. However, the hierarchical structures were comparable when considering only the 26 overlapping sites for the overlapping observation period. The hierarchical structure could be used to predict the stream state based on observations for other sites, allowing us to fill in data gaps. The correlation between the percentage of sites with flowing water and cumulative net precipitation, furthermore, allowed us to extend the prediction of stream states to days for which there were no observations. This study highlights the usefulness of citizen science-based observations of intermittent streams for understanding stream network dynamics. Information on the accuracy of the hierarchy can be used to determine which sites are particularly useful to observe for gap filling and thus to give feedback to citizen scientists.

Plain Language Summary. Streams that do not always contain flowing water form a large part of the stream network and are crucial habitats. However, few of these streams are monitored. Citizen scientists can provide valuable data on when streams are wet or dry. However, these observations are irregular in space and time. This study used data from the CrowdWater app

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with which citizen scientists can report the flow state (i.e., whether there is flowing water or not) for 55 sites across a 4 km² forested area in Zurich, Switzerland. The goal was to predict when sites are flowing or not. For this, we determined the order in which the sites start or stop flowing. Although this order was less certain for the citizen science data than for data collected by an expert, it was similar when considering only overlapping sites and periods. By applying this order to the citizen science data, we could fill in data gaps and predict the steam state for sites that were not monitored based on observations for other sites. Using the correlation between the percentage of sites that had flowing water and precipitation minus potential evaporation, we could even predict the daily variation in flow state for the summer period. Thus, despite some uncertainties, citizen science data can effectively be used to estimate daily variations in flow state across an area.

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1 Introduction

Temporary streams (i.e., non-perennial streams) are streams that do not always contain flowing water. They represent more than half of the global stream network (Goodrich et al., 2018; Messager et al., 2021; Botter et al., 2026) and are expected to increase in number due to climate change and water withdrawals (Dhungel et al., 2016; Sauquet et al., 2021). Temporary streams form unique habitats (Bonada et al., 2020; Sánchez-Montoya et al., 2018; Steward et al., 2022; Stubbington et al., 2017) and are highly dynamic systems (e.g., Ågren et al., 2015). Expansion of the flowing stream network affects hillslope-stream connectivity and, thereby, catchment scale travel time distributions (Botter et al., 2025; van Meerveld et al., 2019), as well as sediment (Fortesa et al., 2021) and nutrient transport (Bujak-Ozga et al., 2024; Larned et al., 2010). Therefore, understanding the patterns of stream network wetting and drying is crucial for the protection of water resources and habitats. However, temporary streams are generally not included in traditional stream monitoring networks (Benstead and Leigh, 2012; Godsey and Kirchner, 2014; Krabbenhoft et al., 2022; Snelder et al., 2013; van Meerveld et al., 2020), due to the lack of gauges for headwater streams where many of the temporary streams are located (van Meerveld et al., 2020), the difficulties in measuring zero or very low flows (Zimmer et al., 2020), and a lack of appreciation of dry streams (Armstrong et al., 2012; Cottet et al., 2023). As a result, repeated detailed information on the flow patterns across the stream network is mostly limited to research areas (e.g., Bujak-Ozga et al., 2023; Jensen et al., 2019; Zimmer and McGlynn, 2017). At these research sites, information on the stream state (mainly wet or dry streambed, but sometimes flowing or not flowing) has been collected by experts who survey the stream network (e.g., Godsey and Kirchner, 2014; Jensen et al., 2017; Sefton et al., 2019), with the help of cameras (e.g., Kaplan et al., 2019; Noto et al., 2024), or low-cost sensors (e.g., Assendelft and van Meerveld, 2019; Bhamjee et al., 2016; Goulsbra et al., 2014; Jaeger and Olden, 2012; Kaplan et al., 2019). In these studies, the stream state was observed either along the entire stream network, or observation points were picked strategically (e.g., equally distributed over the study area, at stream junctions, or at geologically interesting points).

With the help of citizen scientists, information can be gathered about streams that would otherwise have been unmonitored (Njue et al., 2019). In various projects, citizen scientists visually observe the state of temporary streams by either mapping entire stream networks on a specific date (Allen et al., 2019; Turner and Richter, 2011) or by repeated monitoring of specific sites. For the latter, several smartphone applications (apps) have been developed and are used nationally (RIU.NET; www.ub.edu/fem/index.php/en/inici-riunet-en; FLOwPER (Jaeger et al., 2020)) or globally (DRYvER, www.dryver.eu; StreamTracker, www.streamtracker.org; CrowdWater, www.CrowdWater.ch). Typically, citizen scientists decide which stream sites they observe and when. As a result, the data are irregular in both space and time.

Citizen science data are also prone to uncertainties and biases. There are spatial biases related to infrastructure (e.g., road access) and human population density (Geldmann et al., 2016; Mair and Ruete, 2016). Regarding temporal biases, Etter et al. (2020) found no evidence that citizen scientists would only observe water levels on weekends or during nice weather conditions. Instead, the citizen science data covered most of the observed water level range. Still, there are observational biases. Scheller et al. (2024), for example, found that citizens would report a dry streambed, even when they observed pools of water.

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It is, so far, unclear if these biases and the irregular nature of citizen science datasets limit the use of temporary stream observations for statistical modelling and if models can be used to fill the gaps in citizen science datasets for temporary streams.

Crowd-sourced observations of temporary streams have been used in a few studies. Jaeger et al. (2023) applied their previously developed regional Random Forest model (Jaeger et al., 2019) to a National Park located within the area of the regional model. Their model did not predict the timing or duration of flow conditions but allowed them to determine the probabilities of late summer flow and the spatial drivers of flow intermittency. They concluded that crowd-sourced data were useful to improve the results of the regional model. Peterson et al. (2024) installed eleven sensors and additionally used visual observations by citizen scientists collected with the StreamTracker app for 117 sites to predict streamflow durations for the upper part of a large basin in Colorado (USA) based on a random forest model. They found that sites that were observed more than ten times by citizen scientists (112 of the 177 observation sites) were useful for the model and recommended that citizen scientists make weekly stream state observations during summer. Other studies used expert data and random forest models (Beaufort et al., 2019; Jaeger et al., 2019; Kaplan et al., 2022; Moidu et al., 2021; Price et al., 2021; Snelder et al., 2013; González-Ferreras and Barquín, 2017) or principal component analyses (Dhungel et al., 2016; Hammond et al., 2021; Jensen et al., 2019; Paillex et al., 2020) to determine the spatial factors that affect stream drying (e.g., topographic wetness index, soil type, aridity index). While these statistical models are useful to make predictions across large areas, they cannot be used for smaller areas because climate, geology, topography and land use often do not vary enough over a small area to explain the observed fine-scale variations in stream drying. Furthermore, they generally provide limited information about stream network dynamics, and thus the timing of the onset or cessation of flow.

Graph theory has been used to derive the hierarchical structure (or fixed order) of stream wetting and drying (Botter and Durighetto, 2020; Botter et al., 2021; Durighetto et al., 2023; Godsey and Kirchner, 2014). The method is based on the observation that segments usually start to flow in a fixed order during stream network expansion and stop flowing in the reverse order during network contraction (Godsey and Kirchner, 2014) and has been used for a range of catchments (e.g., Botter and Durighetto, 2020; Botter et al., 2021; Durighetto et al., 2023; Durighetto and Botter, 2022). The strength of the method is that it can simulate the flowing stream network and flow permanence based on a relatively small number of stream state observations or irregular larger datasets. This is therefore a promising method to fill gaps in citizen science data for a certain catchment or area. However, it has so far only been applied with data from stream surveys by experts. Although, it has been shown that it can be used with irregular datasets (Durighetto et al., 2023), it is still not clear how well the hierarchical structure can be determined for citizen science data that are generally more uncertain (and more irregular).

Therefore, in this study, we explored the usefulness of citizen science based temporary stream observations for the derivation of the hierarchical structure of wetting and drying and whether this can be used to fill gaps in the data. The citizen science data for temporary streams were collected with the CrowdWater app for a forested recreational area in Zurich, Switzerland. We compared the hierarchical structure obtained with these data with one created based on regular surveys by an expert.

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Additionally, we used the hierarchical structure together with climate data to obtain daily estimates of the stream state for each observation site. More specifically, we address the following research questions:

I. How well can the hierarchical structure of stream wetting and drying be derived from irregular citizen science observations and how does it compare to one based on expert data?

II. Do additional stream state observations by an expert improve the hierarchical structure obtained from citizen science data?

III. Can the hierarchical structure be used to predict the stream state across the stream network based on observations at other sites, and thus fill gaps in citizen science observations?

IV. Can the hierarchical structure, in combination with climate data, be used to obtain daily predictions of the stream state?

2 Methods

2.1 Study area

The study area is a small, forested hill in the city of Zurich, Switzerland (Figure 1a). The 4 km² area, called Zuriberg ranges from 445 to 674 m.a.s.l in elevation. The climate is temperate humid. The surficial geology mostly consists of moraines, although some areas are covered by freshwater molasse (Supplementary material S1). It is mainly forested area and surrounded by residential areas. Due to the proximity to the residential areas, it is frequently visited for recreational purposes. It is highly influenced by human activities. There are, for example, 101 wells for water supply and ~ 57 km of forest roads and paths with ditches and culverts. The natural stream network has been modified, and many streams have small check dams or artificial streambeds (Figure S1).

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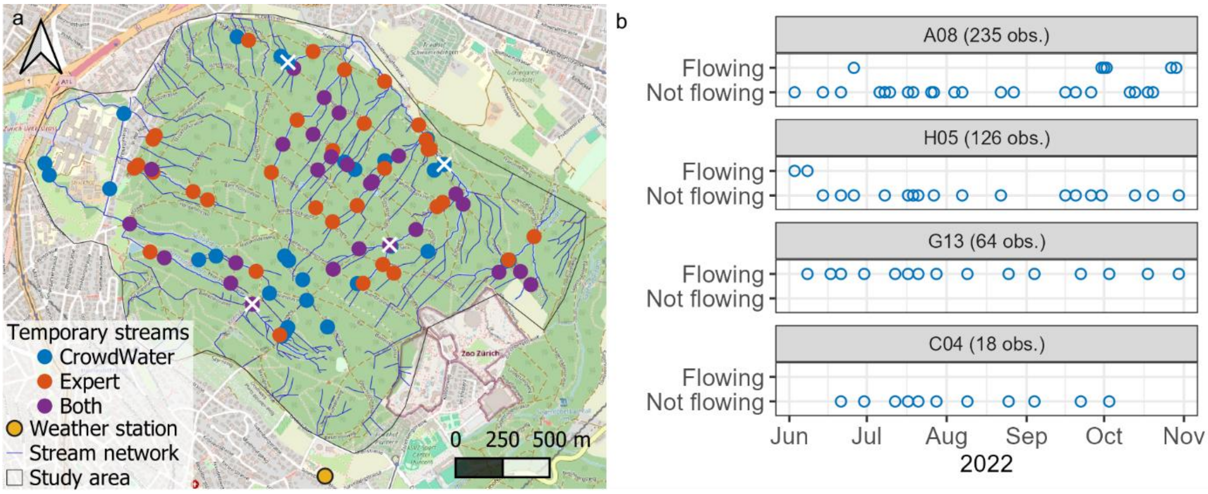

Figure 1: Map of the study area (Zuriberg) indicating the sites where temporary streams were observed (either by citizen scientists (CrowdWater), the expert (Expert), or both (i.e., the Combined dataset)) and the mapped geomorphic stream network (a), and time series of the stream state based on the CrowdWater dataset for four exemplary sites for June to November 2022 (b). The total number of citizen science observations for these sites is shown after the site name above each time series. The location of these sites is indicated with a white X on the map. The four sites were chosen based on the number of observations per site (representing the maximum, and the 75th, 50th (median), and 25th percentiles for the entire dataset) to represent the variety in the data obtained by citizen scientists. A larger version of the map with the IDs of all stream sites and additional maps showing the topography and the geology of the study area can be found in Supplementary material S1 (Figures S2 and S3). The background image for the map is from OpenStreetMap contributors (2017).

Table 1: Description of the different datasets: all CrowdWater data, CrowdWater data collected during the period of expert data collection (CrowdWater$_{short}$), all data collected by the expert, and both datasets combined.

	CrowdWater	Crowdwater$_{short}$	Expert	Combined
Period	Sep 20 – Oct 23	Nov 22 – May 23	Nov 22 – May 23	Sep 20 – Oct 23
Number of sites (nodes)	55	55	59	88
Days with observations	402	48	24	419
Total number of stream state observations	4,360	638	1,416	5,776

2.2. Data and data preparation

2.2.1 Temporary stream observations by citizen scientists

In the CrowdWater app, citizen scientists choose between six different stream states: dry streambed, damp/wet streambed, isolated pools, standing water, trickling water, and flowing (Scheller et al., 2024). They also take a picture of the stream and upload it together with the selected stream state class and gps location in the app. The observations are checked for obvious mistakes (wrong placement on the map, comparison of the selected stream state and the picture, etc.) by members of the CrowdWater team. Repeated observations for the same site lead to timeseries of the stream state for that site (Figure 1b). For the analyses, we merged the stream states into two classes: flowing (trickling and flowing) and not flowing (dry streambed, damp/wet streambed, isolated pools, and standing).

We placed signs across Zuriberg to make people aware of the CrowdWater project and to inform them about temporary streams in the area. Between September 2020 and November 2023, stream state observations were submitted for 63 sites across the Zuriberg study area. A total of 127 citizen scientists submitted the observations. One citizen scientist contributed 62% of the 4,360 stream state observations used in this study, and another one 18% of the observations.

For the analyses, only the sites with at least two observations were used (55 sites). These sites were observed two to 235 times during the three-year period (mean: 79 times, median: 64 times, see Table S1). The observations were irregularly distributed over time (Figure 1b). There was at least one observation for 26% of the days during the study period (mean: 11; median: 10; maximum: 36). The period for which there were no observations for any of the streams on Zuriberg varied between three hours and 20 days (median: 2 days). For 67 days, there was more than one observation per day for at least one site. Only six times did the stream state (flowing or not flowing) differ. This can be the case because the citizen scientists did not agree on the stream state (or one of the citizen scientists made a mistake) or because the conditions had changed between the observations (e.g., the stream started to flow in response to a rainfall event between the two observations or dried up due to evapotranspiration). For these six cases, we used the observation that was made first (i.e., earliest during the day). For 2,294 of the 4,360 observations (53%) the stream state was flowing.

2.2.2 Temporary stream observations by an expert and the combined dataset

One person (Anja Fischer, hereafter named the expert) observed the stream state for 59 sites across Zuriberg on 24 days between November 2022 and May 2023 (approximately weekly resolution). The expert surveyed all 59 sites on each survey date. The sites were selected based on accessibility and suitability for additional measurements (e.g., discharge measurements, data not used in this study), and to cover the variation in elevation, drainage area, and geology. For 26 of these 59 sites, there are also citizen science data (Table 1). The expert used the same stream state classes as the citizen scientists, and these were again merged into the flowing and not flowing categories. For 878 of the 1,416 (62%) observations in the Expert dataset, the stream state was flowing. For comparison, 1498 of the 2545 observations by the citizen scientists for the 26 nodes that were observed by both the expert and the citizen scientists, the stream state was flowing (57%).

We merged the CrowdWater and Expert datasets into a combined dataset (Combined). The stream state in the CrowdWater and Expert dataset did not match six times (i.e., the same site was observed by the citizen scientist and expert on the same day, but they selected a different stream state). Five times the flow state chosen by the citizen scientist was one class wetter than what the expert had observed. Once it was once class drier. These six mismatches occurred only at three sites (one site with three mismatches, one with two, and one with one). For these six mismatches the stream states of the CrowdWater dataset were selected as they matched with the pictures in the CrowdWater app.

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2.2.3 Comparison of the distribution of sites observed by the citizen scientists and expert

We derived the stream network and calculated the drainage area, mean slope, and topographic wetness index (TWI) for each of the observation sites (see Supplementary material S1, Table S1) based on the 2 m Digital Elevation Model (swissALTI3D) from the Federal Office of Topography, using ArcMap (Spatial Analyst Tools) and the raster package (Hijmans, 2010) in R Statistical Software (v4.4.1). The median drainage area was 0.03 km² (range: $0.23 \cdot 10^{-4}$-0.70 km²) for the sites in the CrowdWater dataset and 0.06 km² (range: $0.47 \cdot 10^{-2}$-0.82 km²) for the sites in the Expert dataset. The distribution of the drainage areas for the observation sites matched that of the entire stream network (Figure S5), suggesting that even though the citizen scientists mainly assessed sites at road crossings, there was no spatial bias in the data in terms of the size of the streams observed. The mean slope of the drainage areas ranged from 5-17 degrees for both datasets (Figure S5).

2.2.4 Climate data

Climate data were obtained from the MeteoSwiss meteorological station in Fluntern, located on Zuriberg, less than 2.5 km from all sites in the study area. The daily precipitation for the September 2020 – October 2023 period varied between 0–53 mm/d (mean: 3 mm/d; mean for days with precipitation: 6 mm/d). There was rainfall on almost half of the 1520 days of the full study period (47%). The mean duration of the rain-free periods was 3.7 days (median: 2 days, maximum: 20 days). Snow was observed for 91 days (6%). The mean snow depth for days with snow was 6 cm (maximum: 40 cm on January 15th 2021). The longest period with snow was 12 days in January of 2021. For the other winters, snow cover lasted for only a few days (maximum: 11) and the average snow depth was 3 cm. The mean PET for the study period calculated by MeteoSwiss according to the empirical function of Primault (1962) (based on the relative humidity, sunshine duration and a seasonality factor) was 2 mm/d.

2.3. Hierarchical structure of stream wetting and drying

2.3.1 Development and application of the hierarchical structure

The hierarchical structure of channel network dynamics (cf. Botter and Durighetto, 2020) assumes that there is a fixed, unique order according to which stream segments are rewetted during stream network expansion and that they dry up in the opposite order. Note that the hierarchical structure assumes that the order in which sites start to flow and dry is fixed but that this does not mean that the network expands and contracts in a continuous manner. In other words, it can account for the fact that the drying of stream segments can lead to a discontinued stream network.

To derive the hierarchical order of the stream network, observation sites (called nodes) are ordered by their flow persistence, rather than their physical space. This ordering is summarized by a directed graph, where nodes are connected by links from the most to the least persistent sites based on the available data. For example, if node A was observed to be flowing and node

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B was not, there is a directed link from A to B in the graph and node A will precede node B in the hierarchy. Provided that there are enough observations for all the nodes and the assumption of a fixed order is met, this results in a unique order for all nodes, which can be visualized as a single chain. Some nodes may rewet and dry at the same time as other nodes. For these nodes, the order cannot be derived, i.e., they can take several places in the hierarchy. The mathematical procedure to derive the hierarchical structure of the nodes and to build the graph is described in detail by Botter and Durighetto (2020). The uncertainty of the placement of a node in the hierarchy (δ) is determined by the number of possible positions of a node in the hierarchy that are consistent with the data ($n_{\text{positions}}$) relative to the total number of positions (i.e., number of nodes n_{nodes}).

$$\delta = \frac{n_{positions}}{n_{nodes}} \tag{1}$$

Once the hierarchy graph is built, it can be used to reconstruct the stream state for the nodes that were not observed on a given day by taking advantage of available observations for other nodes. If a node is observed to be flowing, all the previous nodes in the graph (i.e., nodes with links towards the observed node) should be flowing as well because the graph links nodes from the most to the least persistent. Similarly, if a node is observed to be not flowing, all the subsequent nodes (i.e., nodes with links that point away from the observed node) should also be not flowing.

On most days, the stream state was observed for only a few sites and there are thus only data for a few nodes. As a result, the distance between the observed nodes with a flowing and not flowing stream state in the hierarchy may be large. In these cases, no stream state can be assigned for the nodes between the flowing and not-flowing nodes. This leads to uncertainty in the fraction of flowing nodes. Therefore, for all further analyses, we used the median value for all the possible fractions of flowing nodes to account for this uncertainty, which we refer to as the median fraction of flowing nodes.

Even though our study area comprises multiple streams draining the Zuriberg area in different directions, we assume that the small size and small difference in elevation, (Figure S3) will cause the streams in the area to responds to similar driving forces (i.e., input of precipitation) and to respond in a consistent manner, so that we can use a single hierarchical structure for all sites. If instead we were to create a hierarchy for each individual catchment, it would consist at best of only a handful of nodes per catchment. Thus, we used the stream sites as nodes for the directed graph and determined the hierarchical structure for the most to least persistent stream sites for the Zuriberg study area (i.e., not per catchment).

In previous studies (e.g., Botter and Durighetto, 2020; Botter et al., 2021; Durighetto et al., 2023; Durighetto and Botter, 2022), the nodes were associated with a certain stream length because the nodes were placed at strategic locations and were representative for a certain stream segment. We could not determine the stream length associated with each node as the selection of the sites was done by the citizen scientists. Thus, we focused on the fraction of flowing nodes, rather than the fraction of stream length in the analyses based on the hierarchical network.

2.3.2 Comparison and accuracy of the hierarchical structures

We determined the hierarchical structure for different datasets (Table 1): all CrowdWater data (CrowdWater), all CrowdWater data for the period for which the Expert data were also available ($\text{CrowdWater}_{\text{Short}}$), all expert data (Expert), and a dataset that combines the CrowdWater and Expert data (Combined). To assess how the hierarchical structures differ for the different datasets, we compared the hierarchies for:

I. the 26 overlapping nodes of the CrowdWater and Expert datasets (CrowdWater-Expert),

II. the 26 overlapping nodes of the CrowdWater and Expert datasets for the overlapping period ($\text{CrowdWater}_{\text{Short}}$-Expert), and

III. the 55 overlapping nodes of the CrowdWater and the Combined dataset (CrowdWater-Combined).

The comparison of both the CrowdWater and $\text{CrowdWater}_{\text{Short}}$ datasets with the Expert data (I and II) allowed us to separate the effects of the different length of the datasets (and thus different hydrological conditions) from the effect of the differences in the data (i.e., due to errors or inconsistencies in the CrowdWater data, as well as the irregularity of the CrowdWater data).

For each comparison, we visually compared the location of the nodes in the hierarchies to assess the agreement in the relative positions of the nodes in the two hierarchies. We focus on a visual comparison of the ranks of the nodes (rather than a statistical correlation) as not all nodes could be placed in the hierarchy with certainty. The possible positions of the nodes between the datasets in each comparison should overlap if the hierarchies are similar (i.e., do not contradict each other). Therefore, we ordered the nodes by the hierarchy for the CrowdWater (or $\text{CrowdWater}_{\text{Short}}$) dataset using the toposort function in Matlab and included the uncertainties of the placement of the nodes in the hierarchy for both datasets. We, furthermore, compared the hierarchies by calculating the total distance according to Malmi et al. (2015). First, we calculated the transitive closure by adding all indirect links that could be deduced by all available links. If for example, three nodes called A, B and C are ranked in the hierarchy from the most to least persistent (A to B to C), the transitive closure means that A and C are also (indirectly) connected and can be used to derive each other's stream state. We then counted the number of links that were present in both hierarchies but connected the nodes in opposite directions. We refer to this as the total distance between two hierarchies. Finally, we calculated the relative distance by dividing the total distance by the total number of links present in both datasets.

In addition, we calculated the accuracy for each hierarchical structure. The accuracy A of the model is based on the number of true positives (N_{TP}) and true negatives (N_{TN}), where true indicates that the node is flowing and false that the node is not flowing. Thus, if the structure correctly predicts that a node is flowing, it is a true positive (TP) and if the structure correctly predicts that a node is not flowing it is a true negative (TN):

$$A = \frac{N_{TP}+N_{TN}}{N} \tag{2}$$

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where N represents the total number of observations. The nodewise accuracy is the accuracy for a specific node. The timewise accuracy is the accuracy for each day. To interpret the nodewise accuracy for each node, we compared them to the nodewise accuracies derived by a random model (cf., Botter et al. (2021); see Supplementary material S2).

2.4 Relation between the fraction of flowing nodes and cumulative effective precipitation

Previous studies related the fraction of flowing nodes to streamflow to obtain a daily estimate of the fraction of flowing nodes (Durighetto et al., 2022b; Lapides et al., 2021). As the study area has several streams and none of them are gauged, we related the fraction of flowing nodes for the days with observations to a measure of catchment wetness, namely the cumulative effective precipitation $P_{eff,\,T}$, which is the sum of the difference between the daily precipitation (rainfall plus snowfall) and potential evapotranspiration calculated over a period T (cf. Senatore et al., 2021). The precipitation and potential evapotranspiration data were derived from the MeteoSwiss Fluntern station, located on the Zuriberg (see section 2.2.4). In humid temperate regions such as the Zuriberg, actual evapotranspiration is typically close to potential evapotranspiration because water availability is rarely limiting, allowing atmospheric demand (controlled by energy supply, wind, and humidity) to be largely met. Thus, it is reasonable to use the operational PET data from MeteoSwiss to obtain a measure that describes the temporal variation in catchment wetness. For the correlation, we excluded days for which the uncertainty of the fraction of active nodes was >50%. This threshold was chosen to balance the need for a large number of datapoints and to not include very uncertain data. We fitted the skew-normal distribution to the data, as calculated with the psn() function of the sn R package (Azzalini, 2000) (Supplementary material S3) to determine the relation between the fraction of flowing nodes and the cumulative effective precipitation. We chose a non-linear regression because the values should only range from zero to one.

We determined the relation between the fraction of flowing nodes and the cumulative effective precipitation for different periods T, ranging from one to 50 days, and then selected the period for which the residual standard error of the fitted model was the minimum (Figure S6). The optimal period T differed between summer and fall (here taken as June to November) and the winter and spring months (December to May). The residual error was lowest for a 40-day period for the data collected between June and November (0.137) and an 11-day period for the data collected between December and May (0.128) (Figure S7). This difference may in part be caused by snow accumulation and melting (especially in 2021), or the difference between PET and actual evaporation, but also due to the overall general wet conditions in winter and early spring which cause less variability in the cumulative effective precipitation than for summer. For this reason, we use only the observations between June and November (186 days with citizen science observations, including 144 for days for which the uncertainty was <50%) for the final regression. We then used the fitted skew-normal distribution together with the time series of the cumulative effective precipitation to predict the percentage of flowing nodes for each day between June and November. The time series of the percentage of flowing nodes was then used together with the hierarchical structure to predict the daily time series for each node. These predicted stream states for the summer and fall were compared to the observed stream states and those derived by the hierarchical structure for the full CrowdWater dataset to determine the accuracy of the predictions (as described by Eq. (2)).

3 Results

3.1 Hierarchical structure for the CrowdWater and Expert datasets

The hierarchical structure of the observation sites (nodes) on Zuriberg differed for the different datasets. The hierarchy for the Expert data appears overall clearer than for the CrowdWater data (Figure 2). The mean and median uncertainty of the placement of the nodes were higher for the CrowdWater dataset than for the Expert dataset (Table 2). However, for the Expert dataset, the uncertainty was >0.25 (meaning that the node could potentially occupy at least a quarter of all positions in the hierarchical structure) for a third of the nodes (34%). For the CrowdWater dataset, this was the case for only 9 of the nodes (16%). This suggests that there were fewer nodes in the CrowdWater dataset for which the placement in the hierarchy was poorly constrained and that these nodes. Still the maximum uncertainty for the CrowdWater dataset was twice as large (0.62) as for the Expert dataset (0.34). All of the nodes with a high uncertainty were observed less than 25 times (Figure S8).

Table 2: Summary statistics of the hierarchical structures for the different datasets: all CrowdWater data, CrowdWater data collected during the period of the Expert data collection (CrowdWater$_{short}$), all data collected by the expert (Expert), and both datasets combined for the entire study period (Combined). The uncertainty of the placement of a node describes the uncertainty of its placement in the hierarchy (Eq. (1)). The overall accuracy (A) describes the fraction of correctly predicted flow states (Eq. (2)), while the nodewise and time wise accuracies describe the accuracy for a specific node and specific day, respectively. The uncertainty of the fraction of flowing nodes per day is caused by the distance between the observed nodes with a flowing and not flowing state in the hierarchy as no stream state can be assigned for the nodes in the hierarchy between these flowing and not-flowing nodes. The median fraction of flowing nodes is the median value of all the possible fractions of flowing nodes that are compatible with the reconstructed hierarchy and the available observations for a given day. For the number of nodes and observation days per dataset, see Table 1.

		CrowdWater	**Crowdwater$_{short}$**	**Expert**	**Combined**
Uncertainty of the placement of the nodes in the hierarchy [-]	Min	0.05	0.24	0.02	0.01
	Median	0.15	0.45	0.06	0.13
	Mean	0.17	0.53	0.14	0.14
	Max	0.62	1	0.34	0.41
Overall accuracy *A* [-]		0.986	0.979	0.977	0.979
Nodewise accuracy [-]	Min	0.92	0	0.70	0.74
	Median	1	1	1	1
	Mean	0.99	0.97	0.98	0.98
	Max	1	1	1	1
Timewise accuracy [-]	Min	0.88	0.89	0.93	0.87
	Median	1	1	1	1
	Mean	0.99	0.98	0.98	0.99
	Max	1	1	1	1

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Median fraction of flowing nodes per observation day [-]	Min	0.10	0.31	0.39	0.13
	Median	0.53	0.54	0.64	0.56
	Mean	0.51	0.50	0.62	0.53
	Max	0.92	0.88	0.91	0.94
Uncertainty of fraction of flowing nodes per observation day [-]	Min	0.02	0.22	0	0
	Median	0.22	0.40	0.02	0.22
	Mean	0.33	0.48	0.03	0.32
	Max	0.98	0.98	0.17	0.99

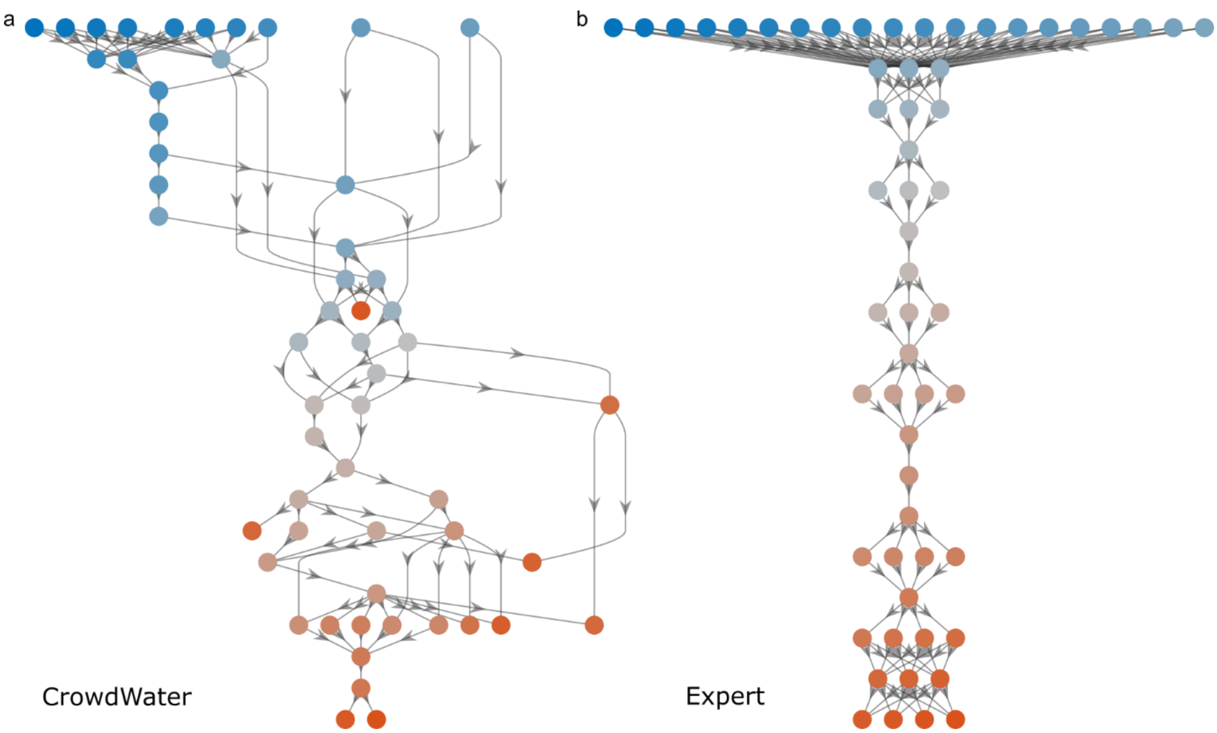

Figure 2: Representation of the hierarchical structure of the nodes for the CrowdWater (a) and Expert (b) datasets. Only the direct links between the nodes are shown in this representation (gray arrows). Nodes at the top of the figure will start to flow first. For the Expert dataset, many of the streams were flowing for all observation dates during the six-month study period and are, therefore, placed next to each other (b). The color of the nodes represents the flow persistence: blue shaded nodes have a more persistent flow (i.e., were observed to flow more often) than red shaded nodes. Especially for the hierarchical structure for the CrowdWater data (a), there are some nodes that have a different color than the surrounding nodes in the hierarchy because their position in the hierarchy is uncertain (i.e., they are plotted at one of the possible positions that are consistent with the data but are colored according to the observed flow persistence). For the order of the nodes' IDs within each structure, see Table S2.

The order of the 26 nodes that the CrowdWater and Expert datasets have in common did not overlap completely for the two hierarchies, even when considering the uncertainties (Figure 3a). For 6.4% of the links that the two hierarchies have in common, the order differed (Table 3). However, if the same period is considered for both datasets, i.e., the CrowdWater dataset is shortened, only one of the links (0.6%) is different and the positions of the nodes in the hierarchy overlap for all

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but two nodes (Figure 3b). The uncertainties of the position of the nodes in the hierarchy for the shortened CrowdWater dataset are, however, high (Table 2).

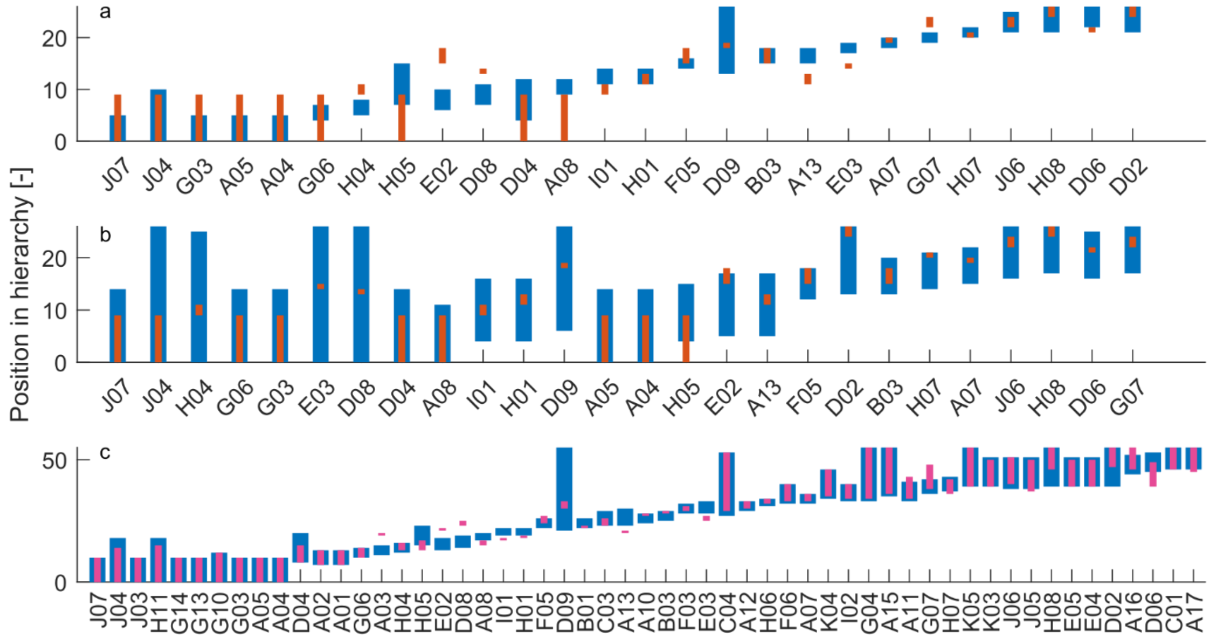

Figure 3: Comparison of the possible positions of the 26 overlapping nodes in the hierarchies for the CrowdWater dataset (blue) and the Expert dataset (orange) for the full dataset (CrowdWater and Expert, a), for the period for which data are available for both datasets (Nov 2022 to May 2023) (CrowdWater$_{\text{short}}$ and Expert, b), and for the 55 overlapping nodes of the CrowdWater and Combined dataset (c). The bars represent the range of positions that are consistent with the data for that node. In other words, a larger bar represents a higher uncertainty of the position of the node in hierarchy. If the bars for the two datasets do not overlap, the position of the nodes in the hierarchy differs for the two datasets. The nodes are ordered according to their location in the directed graph of the CrowdWater dataset, with the nodes on the left side having more persistent flow and those on the right flowing less often (i.e., lower in the hierarchy in Figure 2).

Table 3: Comparison of the links between the nodes of the hierarchies (i.e., the relative node order) for the different datasets. Only the nodes that are part of both datasets are included in the comparisons. See Table 1 for an overview of the data included in each dataset.

	CrowdWater vs. Expert	CrowdWater$_{\text{Short}}$ vs. Expert	Combined vs. CrowdWater
Number of contradicting links between nodes (i.e., total distance)	18	1	20
Percentage of contradicting links between nodes relative to the total number of common links [%]	6.4	0.6	1.6

The overall accuracy A (Eq. (2)) was slightly higher for the CrowdWater dataset (0.986) than for the Expert dataset (0.977; Table 2). For the CrowdWater dataset, the nodewise accuracies were high for all nodes (>0.92) (Figure 4, Table 2). For the Expert dataset, the nodewise accuracy was <0.875 for three of the 59 nodes (i.e., the stream state was predicted wrong for these nodes for three or more of the 24 observation days), with a minimum of. The lowest nodewise accuracy for the Expert

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dataset was 0.70 (Figure 4). For both datasets the nodewise accuracy was higher than for the random model (i.e., a random assignment of flowing and not flowing states that is consistent with the persistence of the node, see Supplementary material S2).

The mean timewise accuracy was very similar for the two datasets (Table 2). There was no seasonal pattern in the timewise accuracy for either dataset. Contrary to the nodewise accuracy, the minimum timewise accuracy was better for the Expert dataset than for the CrowdWater dataset.

For the CrowdWater dataset, the node- and timewise accuracies were not clearly influenced by the number of observations per node or per observation day (Figure S9). This was not analyzed for the Expert dataset because all nodes were observed on the same day and thus had the same number of observations.

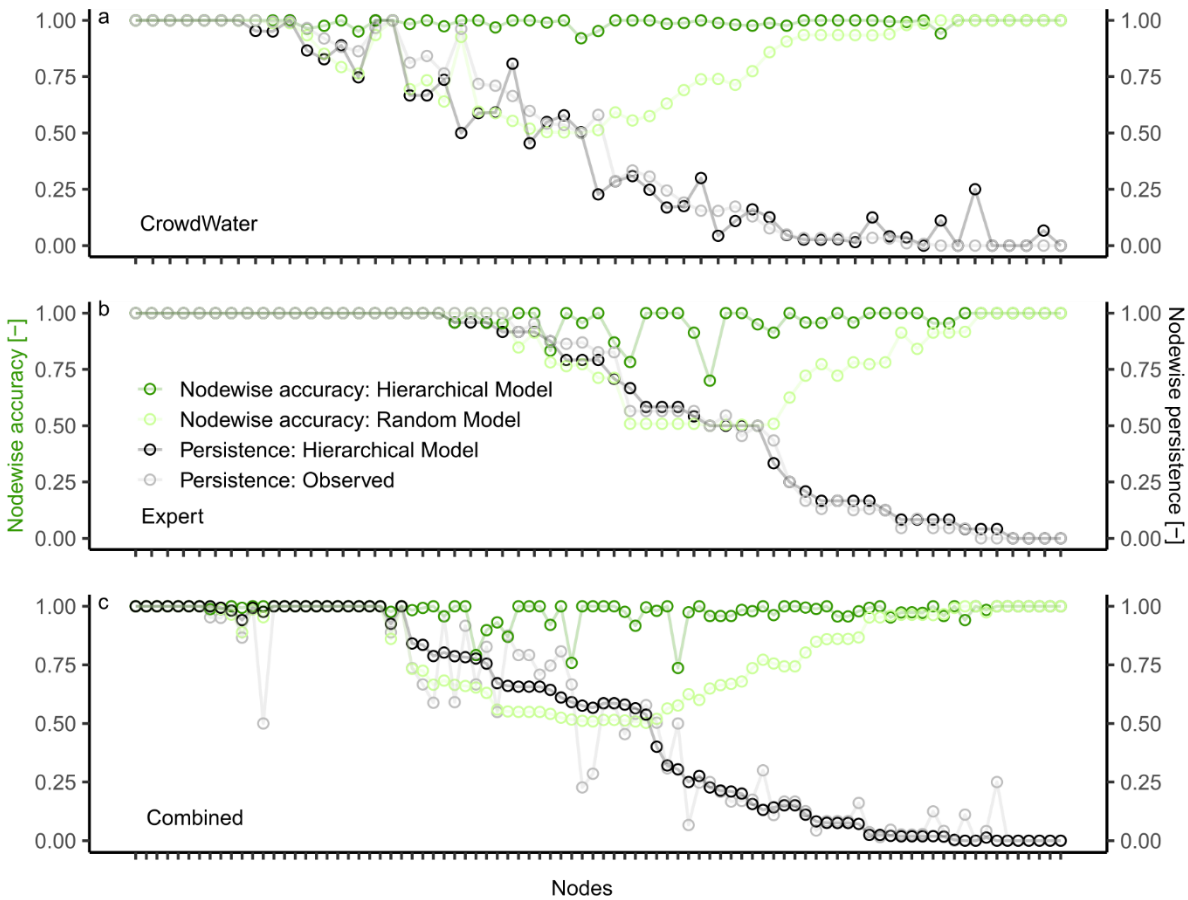

Figure 4: The nodewise accuracy for the hierarchical structure (dark green) and the random model (light green), as well as the nodewise persistence based on the observations (grey) and the application of the hierarchical structure for all days with at least one observation (black) for the CrowdWater dataset (a), the Expert dataset (b), and the Combined dataset (c). The nodes of each hierarchy are ordered according to the order of the nodes in directed graph for each dataset (Figure 2), with those with the most

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persistent flow plotting furthest to the left. A list of the node IDs is provided in Table S2 for each dataset. For the map of the nodewise persistence for the CrowdWater and Expert datasets, see Figure 5.

3.2 Fraction of flowing nodes and flow persistence based on the hierarchical structures

By applying the hierarchy for the CrowdWater dataset to the 402 dates with at least one observation, we obtained the flow state for each node for every day with at least one observation (i.e., 14,695 inferred stream states (84–367 inferences per node, median: 268), compared to the 4360 observations). Because the expert observed all sites on each observation day, the number of the inferred stream states is the same as the number of observations (1,416, 24 per node). Based on these inferences, we can determine the fraction of flowing nodes for each day with at least one observation and the flow persistence for each node.

The nodes located further down the stream network (i.e., with a larger drainage area) had an overall higher flow persistence than nodes located further upstream. This pattern was clear for the observations (Figure S4b) and the inferred flow states (Figure 5). However, there were differences, particularly for the CrowdWater dataset (black and gray lines in Figure 4a). Differences in the persistence for the observations and the inferred state can reflect a temporal bias in the data (e.g., a site was mainly observed during dry or wet conditions) or problems with the hierarchical structure (i.e., a low accuracy).

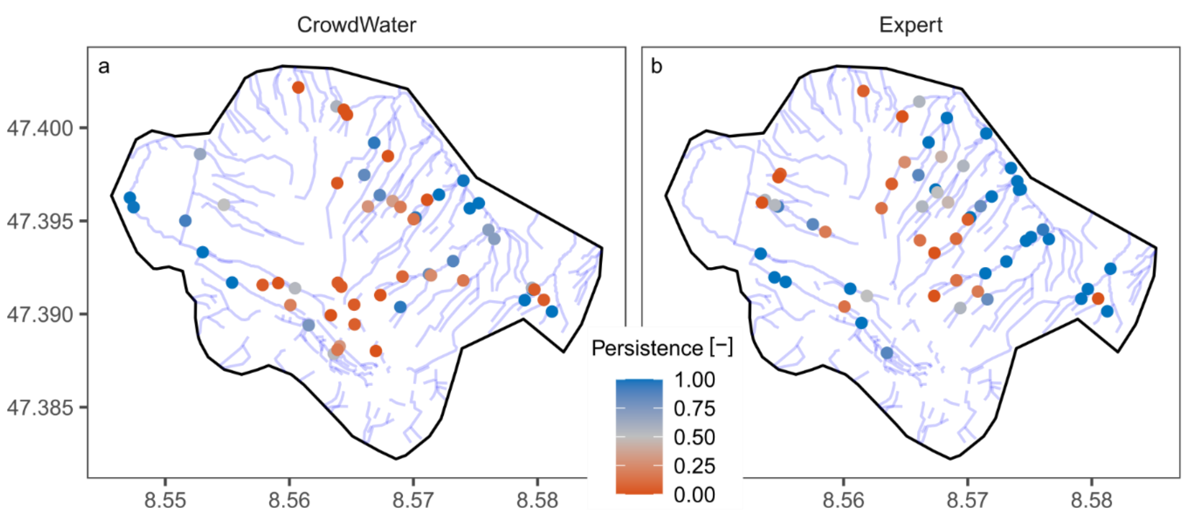

Figure 5: Maps of the nodewise persistence (i.e., fraction of days with at least one observation for which the node was inferred to be flowing based on the hierarchical model) for the CrowdWater (a) and Expert (b) datasets. For the map with the persistence calculated for the actual observations, see Figure S4. The nodewise persistence derived by the observations and by the application of the hierarchical structure are listed in Table S1 for the CrowdWater and Expert dataset.

The inferred fraction of flowing nodes per day (based on the median of the distance between the observed nodes with a flowing and not flowing stream state in the hierarchy, see section 2.3.1) varied more for the CrowdWater dataset than for the Expert dataset because the Expert dataset was collected during a shorter period in which the conditions did not vary as much as during

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the full study period. The lowest median fraction of flowing nodes for the CrowdWater dataset was 0.1 (i.e., only 10% of the nodes were flowing according to the hierarchical structure). For comparison, it was 0.39 for the Expert dataset (Table 2). The inferred fraction of flowing nodes for the CrowdWater dataset were lowest for September-November (Figure 6a). The uncertainty in the inferred fraction of flowing nodes was smaller for the June to November period than the other months, except for September (Figure 6b; Table 2). For 109 of the 402 days (27%) the uncertainty was >0.5. For all days with a high uncertainty, fewer than ten nodes were observed (Figure 6c).

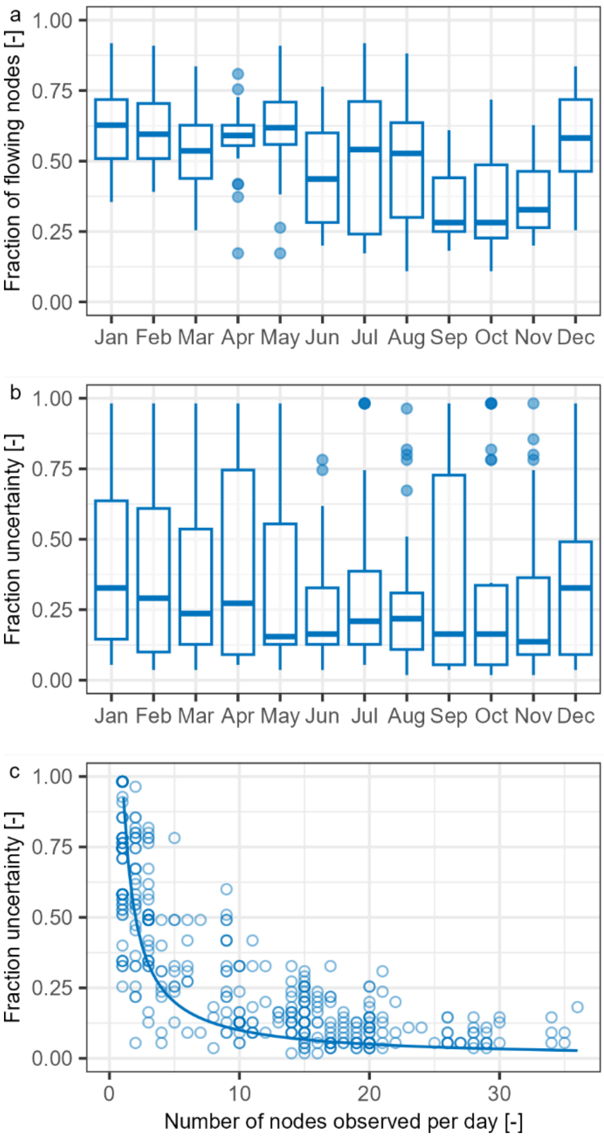

Figure 6: Boxplots of the inferred fraction of flowing nodes for each day with at least one observation based on the median distance between flowing and not flowing nodes in the hierarchy (a) and its uncertainty (b) for each month of the year based on the hierarchy developed with the CrowdWater dataset for the entire study period (Sep 2020 – Nov 2023), as well as the relation between the uncertainty of the inferred fraction of flowing nodes and the number of observations per day (dots), together with aa 1/x functional

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relationship (line) (c). A high uncertainty means that there are many nodes between the nodes in the hierarchy that were observed to be flowing and not flowing for which the stream state cannot be determined. For the boxplots, the box represents the interquartile range, and the thick horizontal line the median. The whiskers extend to 1.5 times of the interquartile range.

3.3 Hierarchical structure for the Combined dataset

Adding the Expert data to the CrowdWater data (Combined dataset) only slightly changed the position of the nodes in the hierarchy (Figure 3c): for only 1.6% of the common links in the hierarchies for the CrowdWater and Combined datasets differed (Table 3). However, adding Expert data decreased the uncertainties of the placement of the nodes for some of the nodes that were observed by the expert (e.g., D09, Figure 3c). All three nodes with an accuracy <0.875 for the Combined dataset were only observed by the expert and had a low accuracy for the hierarchical structure based on the Expert dataset as well.

The overall accuracy of the hierarchy for the Combined dataset was in between the accuracy for the two individual datasets (Table 2). The timewise accuracy for the Combined dataset was also similar and did not differ considerably between the period for which expert observations were available (November 2022 – May 2023) and the remainder of the study period. The uncertainty of the inferred fraction of active nodes, however, was much smaller for the period for which the expert data were available (Figure S10). The median uncertainty of the inferred fraction of active nodes for the Combined dataset for the entire study period was 0.22 (similar to the median uncertainty for the full period of the CrowdWater dataset) but only 0.07 for the period during which the expert made observations (compared to 0.40 for the CrowdWater$_{short}$ dataset) (Table 2).

3.4 Predicted daily stream states based on citizen science observations

The inferred fraction of flowing nodes per observation day for the hierarchy based on the CrowdWater dataset was best correlated with the cumulative effective precipitation between June and November if it was calculated over a 40-day period (Figure 7, residual standard error = 0.128). The number of observations per day did not noticeably influence the relation between the cumulative effective precipitation and the fraction of flowing nodes (i.e., simulations for days with less than ten observations did not tend to be further away from the fitted line than days with more observations; Figure 7). The fraction of flowing nodes varied a lot when the cumulative effective precipitation was between 0 and 100 mm (Figure 7). As a result, the fraction of flowing nodes is overestimated by the skew-normal distribution for October 2022 and underestimated for June 2021 (Figure 8b). In fall 2022 the stream network did not expand in response to the increased cumulative net precipitation, possibly because groundwater levels were still low from the exceptionally dry and hot summer. The fraction of flowing nodes between December and May (which were not included in the regression) has a clearly different temporal pattern and is overall higher than for the months June to November (Figure 8b).

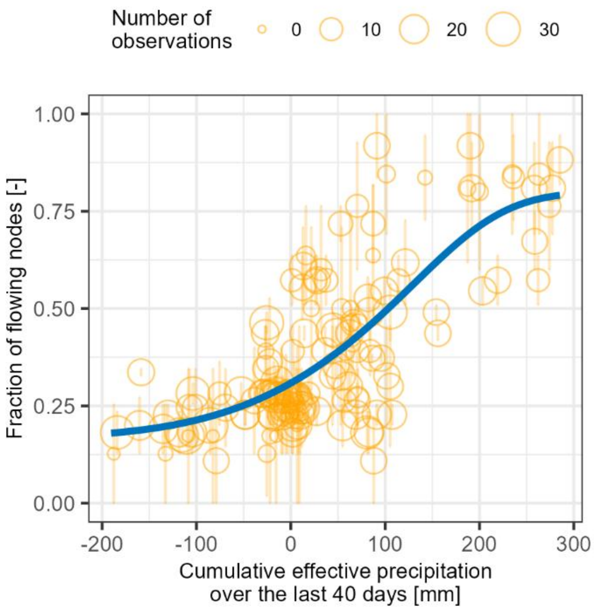

Figure 7: Fraction of flowing nodes per observation day based on the hierarchical structure for the CrowdWater dataset between June and November (yellow circles) plotted as a function of the cumulative effective precipitation calculated over a 40-day period and the best fitted model (skew-normal distribution; blue line). The uncertainty of the inferred fraction of flowing nodes is indicated by the yellow vertical lines. The size of the symbol represents the number of observations for that day.

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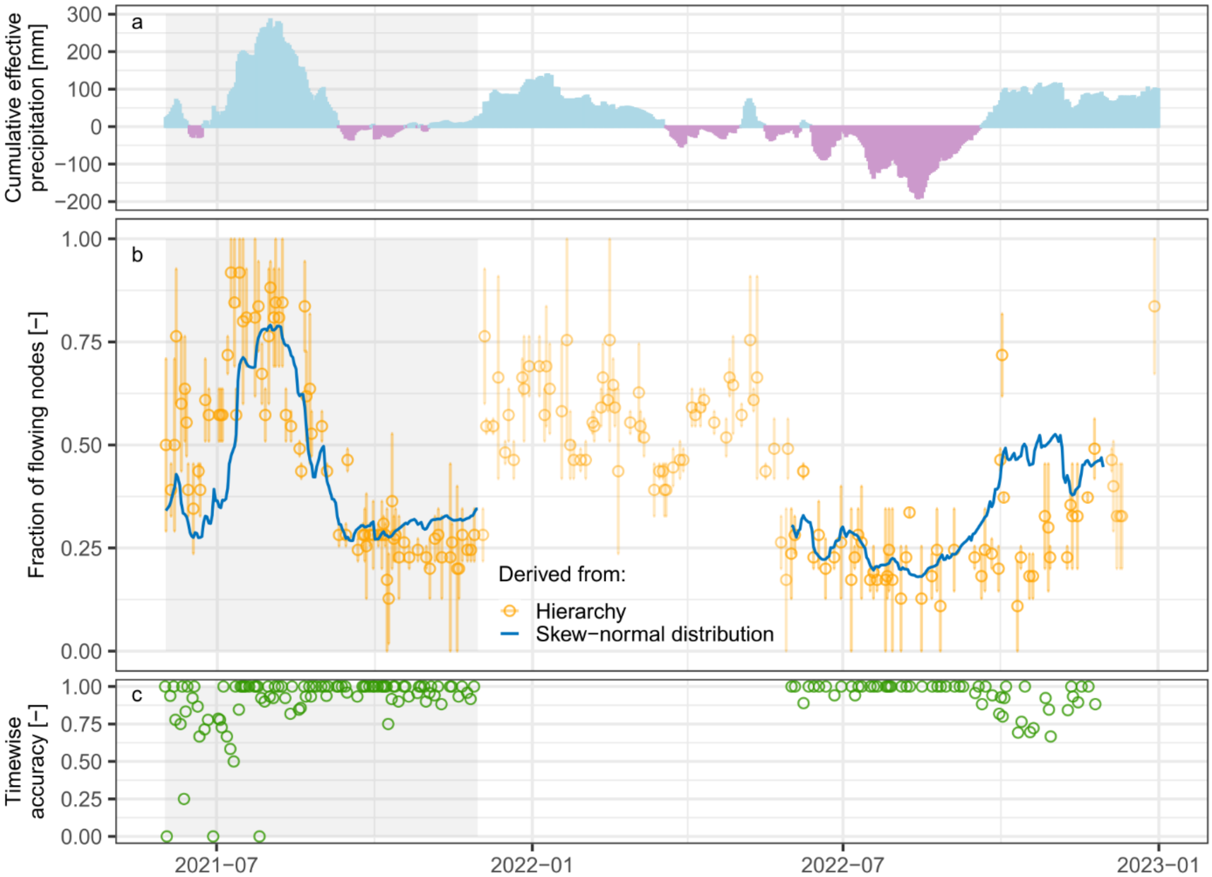

Figure 8: Timeseries of the cumulative effective precipitation over a 40-day period for an exemplary 1.5 year period (a), fraction of flowing nodes based on the hierarchical structure for all days with at least one observation in the CrowdWater dataset and the uncertainty based on the application of the hierarchy for the CrowdWater data (yellow symbols) and based on the regression with the cumulative effective precipitation for the June–November period (Figure 7; blue line) (b), as well as timewise accuracy of the daily fraction of flowing nodes based on to the regression with the cumulative effective precipitation compared to the one derived by the application of the hierarchical model (c). The period shown in Figure 9 is indicated with a light grey shading.

Based on the fraction of flowing nodes predicted by the regression between the fraction of flowing nodes and the cumulative effective precipitation between June and November and the application of the hierarchical structure for the CrowdWater dataset, we could obtain daily predictions of the flow state and fill the gaps in the dataset (all cells marked light orange and light blue in Figure 9). This increased the number of stream states from 6,669 inferenced flow states to 35,569 predicted flow states for the periods between June and November. Although there were some mismatches (dark cells in Figure 9), the overall and nodewise accuracies for the predicted flow states were good (Table 4). However, the timewise accuracy was low for some periods (i.e., for June 2021 and October 2022), in particular for those periods for which the cumulative effective precipitation varied between 80 and 100 mm (Figure 8c). These mismatches compared to the observations are not caused by the hierarchical structure but due to the uncertainty in the relation between the fraction of flowing nodes and the climate data (Figure 7). There

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was no clear effect of the number of observations on the timewise accuracies (Figure S11), nor the nodewise accuracy (Figure 10).

Table 4: Overall-, nodewise-, and timewise accuracies for the application of the hierarchical structure together with the correlation between the cumulative effective precipitation and the fraction of flowing nodes when compared to the actual observations and when compared to the application of the hierarchical structure with the observed data. The comparison with the observations includes errors due to both the placement of the nodes in the hierarchical structure and the regression, while the comparison with the outcome of the hierarchical structure only reflects the errors due to the application of the regression.

prediction vs. observations			prediction vs. inference from hierarchical structure		
Overall accuracy	Nodewise accuracy	Timewise accuracy	Overall accuracy	Nodewise accuracy	Timewise accuracy
0.928	Min: 0.500 Mean: 0.944 Median: 1.000 Max: 1.000	Min: 0.000 Mean: 0.924 Median: 1.000 Max: 1.000	0.958	Min: 0.808 Mean: 0.955 Median: 0.985 Max: 1.000	Min: 0.571 Mean: 0.963 Median: 1.000 Max: 1.000

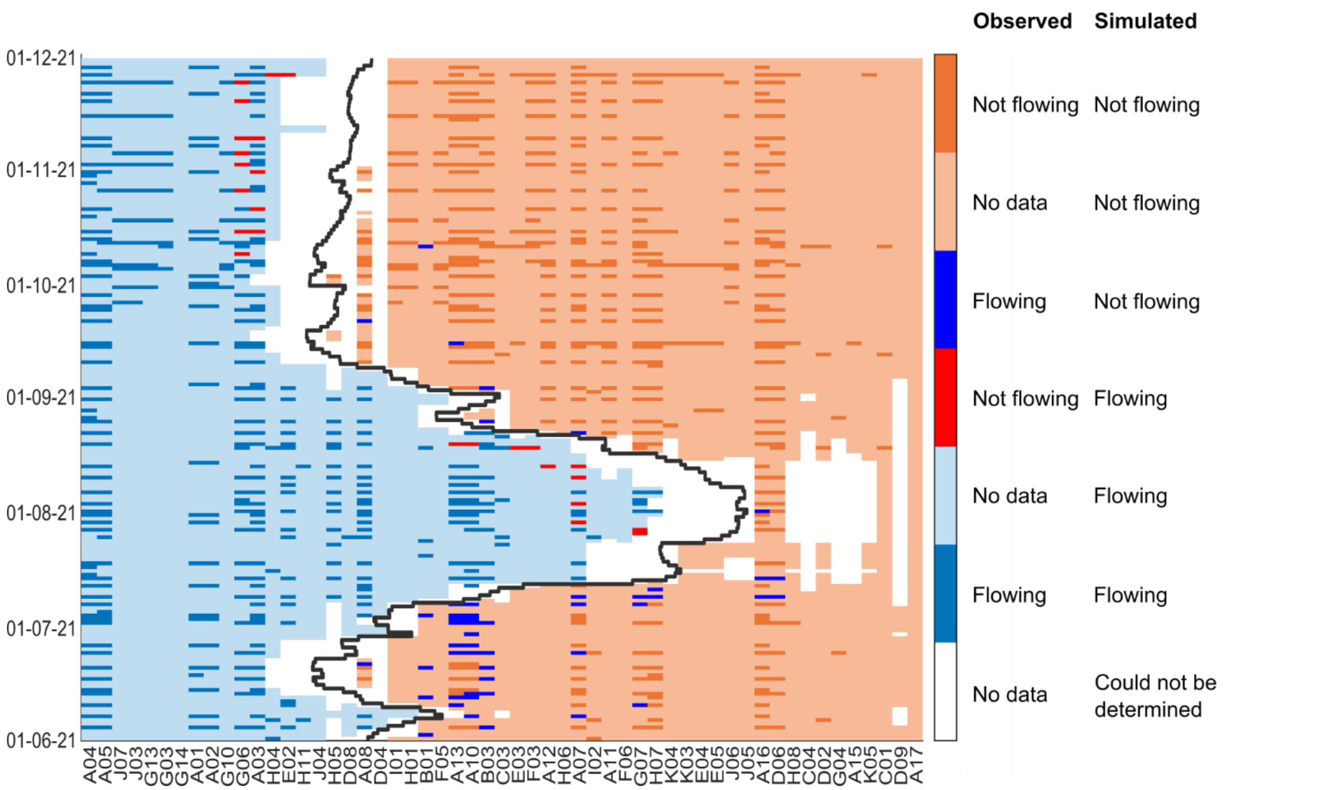

Figure 9: Matrix showing the daily stream state for each node (x axis) based on the regression between the 40-day cumulative effective precipitation and the fraction of flowing nodes and the application of the hierarchical structure for (colored cells) and the fraction of flowing nodes (black line). Observations are represented by a dark color. Mismatches between the observations and predictions are shown in a brighter color (false negatives in red and false positives in dark blue). For the cells marked in a light color the stream state was predicted to be not flowing or flowing, but there is no observation (i.e., the model provided new information).

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Due to uncertainty in the order of the nodes in the hierarchy, the stream state could not be determined for all nodes on all days (shown in white). The period shown here is highlighted in light grey in Figure 8.

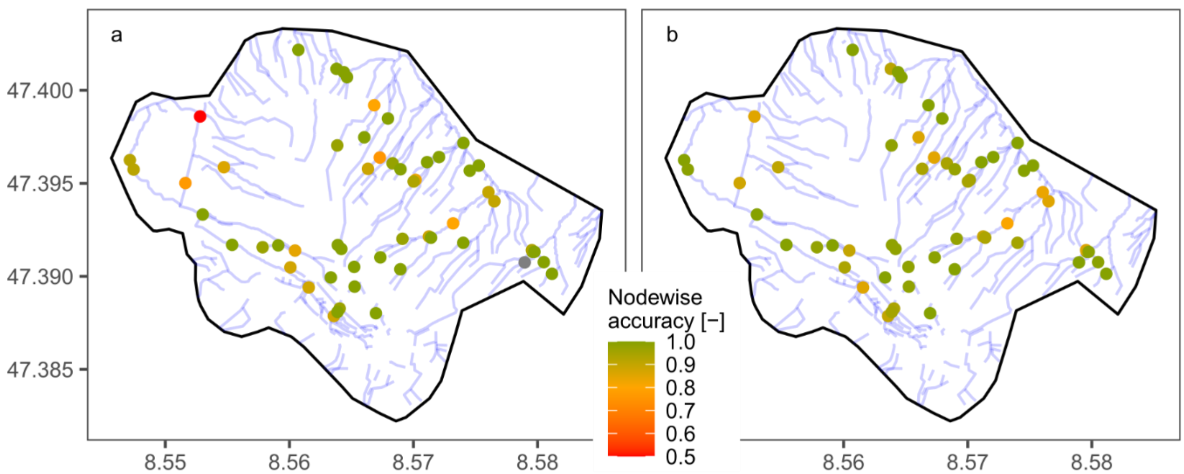

Figure 10: Maps of the nodewise accuracy of the predicted daily stream state based on the regression between the 40-day cumulative effective precipitation and the fraction of flowing nodes and the application of the hierarchical structure developed for the full CrowdWater dataset when the stream states are compared to the observations (a) and to the stream states inferred from the application of the hierarchical structure developed for the full CrowdWater dataset (b). Here, the June to November periods from September 2020 to November 2023 are considered.

4 Discussion

4.1 How well can the hierarchical structure of stream wetting and drying be derived from citizen science data?

The hierarchical structure could be derived from the temporary stream observations made by the citizen scientists (CrowdWater), even though not all sites were observed on each day and there may be inconsistencies in the data because not all citizen scientists interpret stream states similarly (Scheller et al., 2024). The latter is especially an issue when there are pools of standing water, but when the six stream states in the CrowdWater app are regrouped to flowing and not-flowing on average 92% of the people surveyed by Scheller et al. (2024) agreed on the stream state. Thus, the percentage of wrongly classified streams may be relatively small. This is highlighted by the relatively small number of inconsistencies in the data when multiple observations (by different citizen scientists) were made for the same site on one day and between the data collected by the expert and citizen scientists for the same site on the same day.

The overall accuracy was higher for the hierarchical structure based on the CrowdWater dataset was within the range of accuracies reported in other studies (0.94-1; Botter et al., 2021; Durighetto et al., 2023). The accuracy for the hierarchy based on the CrowdWater dataset might have been higher than the one based on Expert data because it had a higher uncertainty. The nodewise accuracy of the hierarchy derived from the citizen science data was high and the median uncertainty in the placement of the nodes in the hierarchy was similar to that for the hierarchical structure based on the regular data collected by an expert. Furthermore, the hierarchies derived for citizen science and expert data were similar when using only the data for the same nodes and the same period. However, the precision of the placement of some nodes in the hierarchy was rather low, especially for nodes that had been observed fewer than 25 times (Figure S8). Therefore, we conclude that despite potentially larger errors and being irregular in space and time, citizen science data can be used to derive the hierarchical structure of stream wetting and drying. It is, however, useful to observe sites at least 25 times. Peterson et al. (2024) recommended at least 10 weekly observations by citizen scientists during the summer months to determine the flow duration curve based on a random forest model for a much larger for a study area in northern Colorado, USA.

The determination of the fraction of flowing nodes was most uncertain for the days with fewer than ten observations (Figure 6c), the December to May period, and September. This pattern is at least in part caused by the variation in the number of observations throughout the year: there were more days with less than ten (but at least one) observations for the December to May period (16%) than for the June to November period (9%). The finding that the number of observations per day has only a small impact on the determination of the fraction of flowing nodes is especially good news when one works with citizen science data because these are generally spotty in nature.

The results of this study can be used to provide feedback to citizen scientists. The nodewise accuracy and uncertainty in the placement of the nodes in the hierarchy can be used to provide guidance to the citizen scientists on what sites are of particular interest and useful to observe. Similarly, the timewise accuracy provides information on when to make observations. The results suggest that it is useful to observe the flow state for at least ten sites per day (Figure 6) to reduce the uncertainty in the determination of the fraction of flowing nodes and that ideally each site is observed more than 25 times to reduce the uncertainty in the placement of the node in the hierarchy (Figure S8). Furthermore, guidelines on when to go out and observe streams can be given, e.g., to determine the order of nodes that were always flowing or not-flowing until that point or to improve the relation between the fraction of nodes that are flowing and a climatic variable that describes the catchment wetness. The outcomes of such feedback would need to be studied in another study.

Whether the results would be similar for much smaller citizen science datasets or data collected in other regions still needs to be determined. The citizen science dataset used in this study is comparable to the datasets obtained by experts in other studies in terms of the number of observations and area covered. Botter et al. (2021) applied the hierarchy to 19 different study sites covering areas between 0.12 and 920 km² (median: 0.37 km²; this study: 4 km²). The number of sites is at the lower end for the CrowdWater dataset but still in the range of Botter et al. (2021) (40–2218 sites, median: 489 sites; this study: 55 sites). The number of observation days (402 days) was much larger for this study (Botter et al. (2021): 7–78 days; median: 7 days). The datasets used by Botter et al. (2021) and Durighetto et al. (2023) were collected in catchments that were not heavily impacted by human disturbances. This study was conducted in a small but heavily impacted area, with in most cases only a few sites per stream. One reason why the method could be applied to this citizen science dataset is that the study area is small

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and relatively uniform in terms of climate and that streams thus respond to the same rainfall events. The area furthermore has a similar landcover and geology. However, Botter et al. (2021) showed for Expert data that the method can also successfully be applied for large, heterogeneous catchments.

4.2 Do additional stream state observations by an expert improve the hierarchical structure obtained from citizen science data?

Adding the expert observations to the CrowdWater dataset did not change the hierarchy considerably, in part because the CrowdWater data already led to a good hierarchical structure. Furthermore, the CrowdWater dataset had three times as many observations than the Expert dataset, so that the influence of the Expert dataset was relatively small. However, the most likely reason is the similarity between the two datasets. The fact that only a few observations made for the same site on the same day differed suggests that both datasets are of similar quality. The uncertainty of the placement of the nodes in the hierarchy improved mainly for the nodes that were part of both datasets. This suggests that additional observations by the Expert (or another citizen scientist) for these nodes improved the placement of these nodes in the hierarchy. However, this was only the case if there are fewer than 25 observations for that node (Figure S8).

Surprisingly, the overall and nodewise accuracy decreased slightly when adding the Expert data due to the inclusion of some nodes for which the nodewise accuracy based on the Expert dataset was low. It is possible that these sites were chosen by the expert because of their special location or response (e.g., they were observed to be flowing when neighboring streams were dry or vice versa). If these sites respond differently to precipitation and dry periods than other sites (e.g., the drying and wetting is not driven by the catchment wetness conditions but by water abstractions), then their location in the hierarchy may change over time and their nodewise accuracy will be low (i.e., they violate the assumption of a fixed hierarchy of wetting and drying). Alternatively, it may be caused by the additional nodes in the dataset and rearrangement of the hierarchical order based on data that only covered part of the study period and wetness conditions.

The timewise accuracies, the fraction of active nodes, and the uncertainty in the fraction of flowing nodes did not change much after the addition of the Expert data. The uncertainty in the fraction of flowing nodes improved when only considering the overlapping period. Thus, to summarize, the overall effect of adding the Expert data was limited. We therefore recommend that experts focus on observing sites for which there are few observations and the placement in the hierarchy is uncertain. Alternatively, the expert or citizen science project leaders could ask the citizen scientists to observe these sites more frequently. The expert could also focus on observing sites that are harder to reach or are located away from roads and hiking paths to avoid some of the spatial biases in citizen science data and obtain a better spatial coverage of sites across the study area. When combined with the citizen science data for the other sites, the hierarchy can then provide information for these difficult to reach places at different points in time.

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The experts could of course also focus on data collection for under-observed periods and conditions. Although this was not a problem for this study because of the large number of days with citizen science data and the overall short periods without any observations. Such additional observations may not only reduce temporal biases in the data but also improve the position of the nodes in the hierarchical structure that were either always flowing or never flowing. Potentially, it can also improve the correlation between the measure used to describe the catchment wetness (here the cumulative effective precipitation) and the fraction of flowing nodes, and thus the accuracy of the predictions.

4.3 Can the hierarchical structure be used together with climate data to fill the gaps in the citizen science data, and thus improve the spatial and temporal resolution of these data?

By applying the hierarchical structure to the observations (for all days with at least one observation), we can obtain information for stream nodes for the days that they were not observed. The results show that the accuracy of this gap filling is high (Table 2). In other words, we can use the hierarchical structure to fill data gaps for stream sites based on observations for other sites (spatial gap filling). In our case, this increased the flow state information more than three times (from 4,360 stream state observations on 402 days to 14,695 inferred stream states for the same 402 days).

The correlation with climate data allowed us to predict the stream state for each site for each day, leading to 35,569 predicted stream states (791 daily stream state predictions for 55 sites minus the 7,936 dates and nodes for which no predictions could be made due to uncertainties in the hierarchy, shown in white in Figure 9). However, the correlation with the climate data has its limitations as there was a large variability in the fraction of flowing nodes for certain values of the cumulative effective precipitation (Figure 7) and because the correlation was poorer for the winter months (Figure S7). We did not have any other data, such as discharge, soil moisture, or groundwater levels (cf. Durighetto and Botter, 2022; Durighetto et al., 2022a; Durighetto et al., 2022b) but expect these measurements to provide a better measure of catchment wetness and to be better correlated to the fraction of flowing stream nodes. The cumulative effective precipitation is not a perfect predictor of streamflow or wetness conditions due to for example time lags or hysteresis in the relation between this measure and groundwater levels. Furthermore, it doesn't account for seasonal differences in interception losses and snow melt during some days in winter. In addition, the study area is characterized by many artificial alterations of the stream network and water abstractions that may influence the relation between cumulative effective precipitation and groundwater levels or streamflow. However, the goal of the analysis was not to find the best model or prediction for the study area, but rather how the correlation between the fraction of flowing nodes and an index that describes catchment wetness conditions can be used together with the hierarchical structure to predict the flow state across the study area. Thus, it is encouraging to see that the number of observations per day had no influence on the correlation and that it was possible to obtain daily predictions of the stream state. Even if the predicted stream state is wrong for some days, the fraction of time that a node had flowing water based on these predictions will be less influenced by the number of observations and the temporal bias in the citizen science data. Indeed, the

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predicted fraction of time that a site was flowing differed from that calculated based on the observations for sites that were observed only a few times (Figure S12).

We could not obtain daily predictions of the fraction of flowing nodes for the entire year as the selected climate variables were not strongly correlated to the fraction of flowing nodes for the winter months. This could be related to the overall fewer number of observations during these months and subsequently larger number of days for which the uncertainty in the fraction of active nodes was >50% (which were excluded from the correlation analysis). Another reason is that the study area was overall much wetter during this period, so that not only the fraction of flowing nodes but also the variables describing the catchment wetness conditions varied less (decreasing the signal to noise ratio). Furthermore, snow accumulation and melt may have affected the streamflow dynamics in a spatially variable way for some days, causing the nodes to respond in a different order than during rainfall events (e.g., factors like aspect and shade may have been more important than during the other months). Finally, it is possible that the PET method, originally based on an empirical relation for grasslands, is not the most appropriate one to use for a forested catchment. Thus, although, we only used the correlation with the effective precipitation for the summer months to highlight the usefulness of the hierarchical structure together with climate data for continuous predictions of the flow state, it will be interesting to test the use of other wetness indices to predict the fraction of flowing nodes (e.g., water balance models that also include snow melt, canopy interception losses, etc., or streamflow or groundwater data).

5 Conclusions

In this study, we derived the hierarchical order of stream wetting and drying for a small, forested area based on observations by citizen scientists. We show that the hierarchical structure was similar to the one based on regular surveys by an expert, although the order of the sites (i.e., the placement of the nodes in the hierarchy) was more uncertain for the irregular citizen science dataset. Combining the citizen science and Expert datasets did not change the hierarchical structure much: it led to a lower accuracy for a few sites but an overall higher certainty in the fraction of flowing streams for the period for which both datasets were available.

Based on the hierarchy, we could fill gaps in the citizen science data and address the temporal bias in the citizen science dataset. By applying the hierarchical structure and filling data gaps for days with at least one observation, we obtained 14,695 inferred stream states from the initial 4,360 citizen science observations. Using the correlation between the fraction of sites with flowing water and the cumulative effective precipitation, we obtained daily predictions of the stream state for all 55 sites (35,569 predictions). This reduces the gaps in the time series for each site and can be useful to obtain more representative information on how often and when each site has flowing water. This reduces the temporal bias in the observations, especially for sites that are observed infrequently.

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Information on the accuracy and uncertainties of the placements of the nodes in the hierarchy could, in the future, be used to identify the stream sites for which additional observations are particularly useful. They can also be used to give feedback and guidelines to citizen scientists (e.g., to observe at least ten sites per day, and to observe each site at least 25 times) and thus to ensure that citizen scientists collect the most useful data possible.

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Author contributions

MS: Writing–original draft, Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Visualization, Project administration.
ND: Writing–review and editing, Conceptualization, Formal Analysis, Investigation, Methodology, Supervision, Visualization
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Competing interests

At least one of the (co-)authors is a member of the editorial board of Hydrology and Earth System Sciences.

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Code and data availability

All CrowdWater citizen science data are available from https://crowdwater.ch/en/data/. The temporary stream data of the citizen scientists (CrowdWater) and the Expert data used in this study will be uploaded to Zenodo [note to reviewers, we will include the link here at the time of publication]. The climate and topographic data are available from MeteoSwiss and SwissTopo respectively (see reference in the text). The code to determine the hierarchical structure is described in Durighetto et al. (2023).

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