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Measuring zero water level in stream reaches: A comparison of an image-based versus a conventional method

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Process understanding of the interaction between streamflow, groundwater and water usages under drought are hampered by a limited number of gauging stations, especially in tributaries. Recent technological advances facilitate the application of non-commercial measurement devices for monitoring environmental systems. The Dreisam River in the South-West of Germany was affected by several hydrological drought events from 2015 to 2020, when parts of the main stream and tributaries fell dry. A flexible longitudinal water quality and quantity monitoring network was set up in 2018. Among other measurements it employs an image based method with QR codes as fiducial marker. In order to assess under which conditions the QR-code based water level loggers (WLL) deliver data according to scientific standards, we present a comparison to conventional capacitive based WLL. The results from 20 monitoring stations reveal that the riverbed was dry for > 50 % at several locations and even for > 70 % at most severely affected locations during July and August 2020, with the north western parts of the catchment being especially concerned. Thus, the highly variable longitudinal drying patterns of the stream reaches

Abbreviations: WLL, water level loggers; IRES, intermittent rivers and ephemeral streams; T, threshold.

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could be monitored. The image-based method was found to be a valuable asset for identification of confounding factors and validation of zero level occurrences. Nevertheless, a simple image processing approach (based on an automatic thresholding algorithm) did not compensate for errors due to natural conditions and technical setup. Our findings highlight that the complexity of measurement environments is a major challenge when working with image-based methods.

KEYWORDS
zero flow, streamflow intermittency, hydrological drought, innovative sensors, longitudinal connectivity, stream reaches

1 | INTRODUCTION

Extreme low flows during drought affect water availability, quality and the aquatic ecosystem (Leigh and Datry, 2017). Their most extreme form is a partial or full drying-up of streambeds. Rivers with periodic and temporary streamflow are classified as Intermittent Rivers and Ephemeral Streams (IRES). The proportion of IRES in the global river network is estimated at 30 % excluding and 50 % including headwater streams (Fortesa et al., 2021; Costigan et al., 2016). Regime shifts from perennial to intermittent streamflow are estimated to occur more often in the future, also on the Northern Hemisphere (Petra Döll and Hannes Müller Schmied, 2012). Streamflow intermittency can have severe consequences for riverine ecosystems, especially where aquatic biota is not adapted to this temporary drying (Acuña et al., 2020; Leigh and Datry, 2017). To capture the dynamics of streamflow recession and rewetting in intermittent and ephemeral streams IRES, the measurement of the hydrological state of the streams (water, no water, flow, no flow) is of particular interest (Meerveld et al., 2020; Datry et al., 2017). Continuous observation and monitoring of stream reaches and tributaries is vital to obtain more data on IRES. In global hydrometric datasets, however, stream reaches and streams with a mean annual flow $< 50\ m^3\,s^{-1}$, with a snow cover of > 75 % in the upstream drainage area and streams in extreme climates are likely to be underrepresented (Messager et al., 2021). Due to this data gap, simulating and predicting streamflow intermittency has often been based on spatial predictors, such as topography, slopes or drainage area, transmissivity (Kaplan et al., 2019; Olson and Brouillette, 2006) and has often been validated using hydrographic maps or field mapping (Botter and Durighetto, 2020; Zimmer and McGlynn, 2017).

The collection of hydrometric data for smaller streams is therefore indispensable especially for purposes such as environmental flow modeling or global mapping of intermittent rivers. However, a water level measurement is taken at one isolated point in a stream crosssection. In practice, many gauging stations make use of water level data and additional streamflow measurements to calculate streamflow at any given time based on rating curves. Moreover, zero flow and zero water level measurement is challenging with conventional techniques because installation errors, data errors and ambiguity hinder a correct interpretation of zero flow readings (Zimmer et al., 2020; Heiner et al., 2011). The heterogeneity of the stream bed, which is subject to a strong variability due to changing flow conditions and sediment transport may lead to erroneous zero flow or zero water level measurement. Measurement of zero-water levels remains difficult, for example if ponding occurs locally along the river section. As long as the occurrence of zero-flow or zero-water level is not measured with sufficient accuracy and temporal and spatial resolution, the potential to use

modeling for water resource management and the prediction of drought and low flow is restricted because validation and calibration of model results require reliable hydrometric data (Hannah et al., 2011).
The development of non-conventional sensors for monitoring is useful to gather more observational data in tributaries and stream reaches. The simple installation of such in-situ sensors in remote areas, their potential to measure continuously with high resolution, the affordable cost and therefore also less risk of financial losses in case of damages occurring under changing natural conditions make them an appropriate alternative to conventional methods (Chapin et al., 2014). Electrical conductivity and temperature loggers (Larson and Runyan, 2009; Peirce and Lindsay, 2015; Zimmer and McGlynn, 2017; Zanetti et al., 2021; Bhamjee et al., 2016; Blasch et al., 2002) and float switch or flow sensors (Assendelft and van Meerveld, 2019) have been successfully used to monitor state changes of small headwater streams and stream reaches. The use of remote sensing is often proposed to study connectivity of stream networks for ungauged catchments and areas suffering from data scarcity (Stoll and Weiler, 2010; Gleason and Smith, 2014). Disadvantages are however the low temporal resolution, data gaps due to obstacles such as cloud cover (Spence and Mengistu, 2016). In general, aerial surveys are not applicable in areas with dense tree cover along streams (Roelens et al., 2018) and vegetation, leading to misinterpretation due to moisture (Spence and Mengistu, 2016; Eltner et al., 2018).
On-site image-based techniques are increasingly applied for monitoring as they contain an additional visual information and thus reduce the probability of misinterpretation (Leduc et al., 2018). Another advantage is, that they do not require on-site calibration (Gilmore et al., 2013; Kaplan et al., 2019). (Young et al., 2015; Leduc et al., 2018) detected the edge position of streams manually and assume that each edge coordinate is linearly related to the water height. Furthermore, they used a width-stage relationship to derive streamflow. In addition, not only water level, but also water velocity observations are possible using short videos and particle image velocimetry (Perks et al., 2020; Piton et al., 2018). Another option to obtain information on the water level or streamflow is to use image pattern recognition algorithms (Eltner et al., 2018; Elias et al., 2020; Eltner et al., 2021). Staff gauges (Seibert et al., 2019; Strobl et al., 2020; Bruinink et al., 2015) or fiducial grid patterns (Gilmore et al., 2013; Kaplan et al., 2020). Citizen science and crowd-based water level measurement have received rising attention in recent years (Simon Etter et al., 2020; Strobl et al., 2020; Seibert et al., 2019) because they are a valuable extension to monitoring data, especially with regard to the lack of data on IRES. While citizen science approaches reduce errors related to measurement installation and maintenance, the information is not collected during fixed time intervals and the information content may deviate depending on the person who collected the data. The use of fiducial markers therefore also holds potential for enhancing the quality of data collected with citizen science approaches because it transports an exact value when recognized correctly.
The catchment of the Dreisam river in south western Germany is known as a perennial river; But its tributaries as well as parts of the upper and lower main stream can fall dry during extreme meteorological drought events, such as in the years 2003 and 2018 (Erfurt et al., 2020). The main gauging station, located in the Dreisam Valley at Ebnet, a subdivison upstream of the city of Freiburg, has been found not to be representative of water level and flow conditions across the basin during hydrological drought or low flow (Blauthut et al., 2017). Until a recent reconstruction of the station's crosssection (Baden-Württemberg, 2021), zero water levels could not be derived from the multiple decades-long time series of hydrometric data from the main gauging station in the valley due to uncertainties for recordings of water levels below 20 cm. A modified rating curve is not yet available. In addition, hydrological dynamics of different river reaches might be different in comparison to the location of the gauging station depending on the hydraulic properties and the geometry of the riverbed and its interaction with the groundwater. Hence, the main gauging station has provided little indication of the true dry river conditions in the valley. To better understand the drying pattern in the catchment a network of water level gauges was installed and allowed to monitor a hydrological drought event in

2020.
With this study we aim to address three research questions:

1. Is it possible to use an image based method for water level measurements based on QR-code detection?
2. What are problems and possible causes related to a QR-code image based water level logging?
3. Is it possible to identify zero level occurrences and drying patterns of the stream reaches using the specific measurement techniques?

Due to the aforementioned challenges when measuring zero water level more knowledge on the suitability of different measurement methods is needed. In this study, we therefore compare the time series of two different measurement methods: an image-based measurement method using QR-codes as fiducial markers and a conventional capacitive Water Level Loggers (WLL) technique. We explore the range, temporal evolution and the correlation of the water level time series measured with both methods at 11 locations in the study area. Subsequently, we identify potential error sources for the measurement of zero water levels using image-based WLL and propose specific corrections for different error sources. We then implement a method to determine zero water level occurrences and use the image-based method as an additional source of information to validate the event selection.

2 | METHODS

2.1 | Measurement approach

Image-based measurements have been used more often in recent years to measure water levels (Gilmore et al., 2013; Kaplan et al., 2019). The additional visual information contained in each image provides an additional possibility to validate the dry status of the riverbed. In order to obtain an information on the water level, a reference point or fiducial marker is necessary. Due to numerous industrial applications of QR-Codes, a selection of open source libraries (Abeles, 2016; Hudson et al., 2015; Abeles, 2013) is available for the detection of QR-codes, which makes it a realistic target to use QR-Codes as fiducial marker for the measurement of water levels. In our measurement setup we used

FIGURE 1 Measurement setup Wagensteig tributary summer 2020

TABLE 1 Main properties of the measurement methods

	Image-based WLL	capacitive WLL
Method	**QR**	**Ody**
Data transmission	manual	manual
Accuracy	3 cm	±0.5 cm
Data Processing	yes	no
Pre-/Post-Processing	yes	no

QR-codes as fiducial markers (Figure 1). The QR-Codes are printed onto a HPL (high pressure laminat) panel (dimensions 60*x*85cm). Each QR-Code covers 10*x*10cm. The horizontal distance between the codes is 44 mm and the vertical distance is 20 mm. Between the columns, there is a vertical offset of 33 mm. A key factor for the choice of the size and placement of the QR-codes is to find the optimal compromise between picture resolution and the distance between the camera and the panel. Each QR-code represents a distinct water level of 0 – 72 cm in steps of 3 cm (a total of 25 QR-codes per panel) (Figure 1, Table 1). With this QR-code configuration, the water level can thus be measured at a maximum accuracy of 3 cm. The lowest QR-Code recognized by the software is representative for the water level. The camera used is a DOERR SnapShot Mini 5.0 wildlife camera and measures at an image resolution of 8 MP. During nighttime, the camera automatically switches to infrared mode while lowering the resolution. The cameras take an image every 15 minutes. This high temporal resolution was chosen to capture fast water level rise and recession. A battery with an initial electric potential of 6.5 V and an electric charge of 4.5 A h was used.

A variety of software is available to read QR-codes due to the numerous applications of QR-codes in industry and other sectors (a comparison of the performance of different software for QR-code detection is available online (Abeles, 2018)). The QR-codes are read using the python wrapper pyboof for the java library BoofCV (Abeles, 2016). The package detects the positioning detection markers of a QR code and the alignment markings. According to a performance evaluation of the provider, BoofCV is able to read multiple QR codes in one image, while the processing time is not longer than with other packages. For all of the available QR code software, damaged QR codes, images with bright spots and non-compliant QR codes are problematic for detection performance of the software. The package can also be implemented on Rasperry PI which is promising if automatic data transmission is envisioned in the future. Additionally, an android app is already available for BoofCV.

The second method used in this study is a capacitive water level observation. Therefore, an Odyssey Capacitance water level logger (Ody) (Ltd, 2013) was additionally installed at every measurement location. Measured is the capacity of a condensator consisting of a teflon coated wire and the water in the river bed. Teflon coating is the dielectric between the wire and the water. The higher the water level, the larger is the plate of the condensator and thus, the higher the measured voltage. The Ody Loggers can measure with an accuracy of ±0.5 cm and do not require data processing in contrast to the QR measurements (Table 1). Each logger was calibrated in a laboratory environment according to the manual. Ody loggers were installed in the field using PVC pipes (Figure 1) in order to compare the image-based to a capacitive (conventional) measurement method with regard to their suitability for measurement of zero water level. Considering the technical properties of both measurement methods alone, QR has a lower accuracy and requires also more effort for post processing (Table 1).

2.2 | Image processing

Errors due to image-based water level measurements can be classified into three categories according to (Gilmore et al., 2013): Errors due to the quality of the pictures (also mentioned in (Leduc et al., 2018)), due to local environment (light conditions) or due to software and image recognition. An option to reduce the effect of the errors on the final data set, a possibility is pre- or post processing of the images. In order to find a methodology for pre- or post processing, it is necessary to know how the software deals with these error types. In the case of images with over exposure and strong light reflections, the software will not recognize any QR code and ultimately issue a NAN value. Post processing is thus not needed and the erroneous values can be excluded without much effort. However, preprocessing might be valuable in order to reduce the duration for reading of the images. Images with overexposure and strong light reflections can be filtered using a threshold on the gray-scale image for bright colors. Major inaccuracies in the water level data set however, are caused by images with few light reflections and with sediment accumulation. In such cases, the information on a single QR code is lost where light reflections or sediment accumulation occur but the software still reads the remaining QR codes. Sediment accumulations occur most likely on the bottom of the QR code panel below the water surface and deposits remain on the panel once the water level decreases. Where sediment

accumulation occurs, the resulting measured water level will thus be biased towards higher values in comparison to the actual, true water level. This may also be the case for images with few light reflections, if those appear on the bottom of the visible part of the QR code panel right above the water surface.
We wanted to know if it was possible to identify images concerned by sediment accumulation or light reflections with a multi-threshold approach. Hereby, multiple thresholds are defined based on the intensity of gray scale values of the pixels in an image. Thus, the different pixels can be classified into different "regions" based on these thresholds. Ideally, the pixels concerned by an error source (i.e. by sediment deposits or light reflections) belong to one specific region. If the number of pixels in an image belonging to this specific region is large, the image is most likely affected by the error source and can be pre-selected. This method could be either applied as a pre- or post processing strategy.
In this study, we used images with sediment accumulation, strong light reflections, relatively few light reflections and overexposure as a benchmark in order to demonstrate in which cases, a multi threshold approach may be useful to filter images that are subject to error sources. The thresholds can either be specified manually or using an algorithm for automatic thresholding. Due to their accuracy and speed, algorithms that are calculating thresholds by maximization of between class variance (Otsu's method) are commonly used (Kotte et al., 2018; Otsu, 1979). Here, we use a Multi Otsu threshold with 5 classes. The benchmark images as examples with the corresponding histograms and the resulting colored regions are shown in Figure 2.

To identify overexposure and light reflections, the pixels in region 4 and to identify sediment accumulation, the percentage of pixels with respect to total pixels in region 3 was calculated (Table 2). The results show, that it is

TABLE 2 Counted pixels per region

Error source	Region	Pixel (%)
Normal	3	12.01
Sediment accumulation	3	11.38
Normal	4	20.27
Light reflections	4	16.01
Strong reflections	4	44.84
Overexposure	4	44.88

possible to distinguish between strong overexposure or strong light reflections and normal conditions. However, it is not possible to distinguish between normal conditions and sediment accumulation or few local light reflections in the image. The filtering of such images is complex and therefore, a specific methodological approach needs to be applied rather than a simple algorithm for automatic thresholding.
Few light reflections occur likely at the start or at the end of the time window, during which light reflections and overexposure occur. An algorithm, that compares the threshold of a particular image to the prior or following image taken could probably be useful to identify time windows during which light reflections occur automatically. There may be other image processing techniques that could be applied but it is out of the scope of this study to develop a new methodological approach.
Due to the complexity of filtering the QR code images and the lower accuracy in comparison to the Ody measurements (which would call for an entire study of its own), we used only the Ody data for data analysis and selection of zero level occurrences. However, we can make use of the visual information in the images in order to validate the zero level occurrences based on the Ody data.

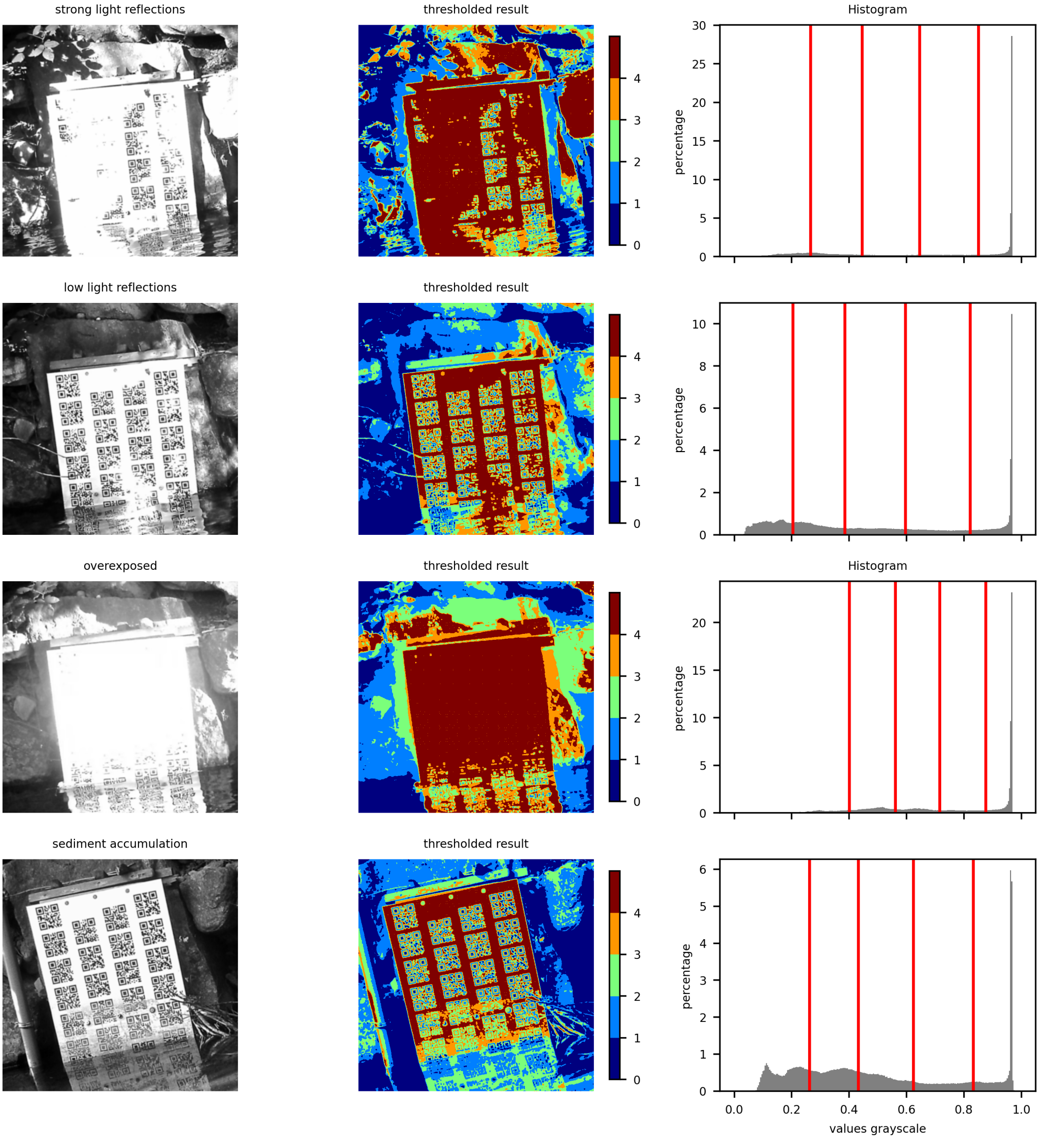

FIGURE 2 The benchmark images from the different error sources, histograms with thresholds and the resulting classification after Multi-Otsu Thresholding

2.3 | Zero water level identification

The water level (often also refered to as river stage, water height, stage height) is described as the perpendicular distance from the bottom of the riverbed to the water surface. Zero water level is the status where no water is left in the whole riverbed's cross section. More specifically, this means that there is no more water present at the deepest point of the river cross section and, that there is neither flowing nor standing water present in the riverbed. For the characterisation of IRES, the status information (dry, standing water, flowing water) is particularly important (Datry et al., 2017; Meerveld et al., 2020). With the measurement methods used in this study it is not possible to determine the status change from flowing to standing water. Furthermore, the measurement devices are installed at one specific point along the river at the border of the river bed next to the river bank and the water level is therefore only measured directly at this spot. Ponding can not be directly measured if the measurement device is not located at the deepest point in the river bed section, which may change after each sediment transport event.

If there is a vertical offset between the deepest point of the river bed and the location of the measurement device, it is hard to distinguish if the riverbed is entirely dry or if it is only dry at the borders while standing water remains at the deepest point. To make a distinction here, the water level, at which the water is likely standing and not flowing anymore needs to be known. However, the point of no flow is site specific as it depends largely on the hydraulic properties and geometry of the river section (and not only on the cross-section of the river bed) and therefore, the generation of a rating curve for each location is a prerequisite. This should be kept in mind if any of the presented methods are used to establish a data-set of zero water levels.

Potential sources of inaccuracy for both measurement methods can be due to measurement installation and measurement principle. Specifically for the QR method, a software is required to read the images in order to obtain an information from the fiducial markers on the images. The result of the measurement thus also depends largely on the quality of the image, the local environment (light conditions) and on the software and image recognition algorithms used (Gilmore et al., 2013). The quality of the image and the chances for recognition of the fiducial marker also rely on the ratio of the distance of the panel and the camera and on the focal point.

In order to measure zero water level with the measurement methods used in this study, corrections are required for both, the capacitve and the image based method. Corrections of the QR data can be needed for specific locations where the panel position is not vertical and where there is an offset between the bottom edge of the panel and the bottom of the river bed. However, specific care was taken in order to avoid inclination and a vertical offset of the QR panels and accordingly no offset correction was required for the QR data.

An offset correction was however necessary for the Ody data. The Ody loggers are hanging vertically in PVC tubes without direct connection to the bottom of the river bed. Also, water levels measured by the Ody loggers may overestimate water levels for low electrical conductivities. A small, positive offset of the Ody measurements is therefore expected. To take this offset into account, we applied a correction based on the minimum in the time series. This means that a low water level between 0 – 10 cm is measured once the water level reaches zero. A correction of this offset can either be done manually using the pictures from the cameras installed at most of the stations or by defining an offset. Here, the latter was chosen and the offset was corrected by the mean of the minima in the Ody water level time series for all stations, where a minimum value below 10 cm had been measured. Additionally, a general source of uncertainty for the Ody measurements is, that the loggers are sensitive to soil moisture. This could result in a time lag between the true occurence of zero water level and the actual, recorded zero water level. Here, we assume that the additional visual information could be helpful to determine the time lag.

2.4 | Measurement comparison

The main objective of this study is the distinction between different error sources of an image-based and a capacitive water level logging technique with regard to measurement of zero water level. For this purpose, we use a comparative

approach and we consider that a correction using the deepest point in the river bed is not required. A comparison to the main gauging station in the catchment is not possible due to the particular situation, that it was not suitable for measuring low flows before 2019 and it could not be excluded that reconstruction still affected data collection in 2020.
In a first step we compare the performance of the measurement methods with regard to data availability, time and effort for maintenance as well as for the evaluation and data handling.
Furthermore, we inquired if there is an association between the water levels measured with both methods. A general measure to investigate the strength and direction of an association between two variables is the correlation coefficient R.

Here, we calculated the Spearman rank correlation for a rolling window with a window width of 96 steps (equals 1 day). If the spearman correlation indicates a perfect correlation, the relationship between the two variables is represented by a monotonic function. This allows to evaluate whether the water levels are rising or falling at the same moment or not within the time interval of a day and if this association changes over the course of time.
Subsequent to the method comparison and the corrections, a method for filtering of zero level occurrences from the available time series is presented. Zero level occurrences were selected based on the choice of a threshold and the coefficient of variation. First, the Threshold (T) was defined as the sum of the minimum and 5 % of the maximum value in the time series:

$$T = x_{min} + 0.05x_{max} \tag{1}$$

with x_{min} and x_{max} being the minimum and maximum in the time series at each measurement location. In a next step, the coefficient of variation based on a hourly mean (or daily mean) was calculated. If the variation remained below 0.1 with respect to the hourly mean for at least 4 hours at a specific time, it was considered that zero water level occurred. Furthermore, the additional visual information contained in the QR images allows a validation of zero level occurrences for each location. Therefore, the images corresponding to the date and time of the zero level occurrences were filtered at first. Secondly, images were visually inspected and classified as "dry" and "not dry". Hereby, a dry riverbed corresponds to the status where there is neither standing nor flowing water visible in the image. Finally, the percentage of images (among a random choice of 10 % of all images) recognized as "dry" defines if the validation was successful or not.

3 | THE STUDY AREA

The Dreisam catchment covers a total area of 577 km^2). Figure 3 shows the total extension of the catchment and the locations of the measurement devices in the Dreisam valley (25 km^2). The porous aquifer consisting of alluvial materials with 30 – 50 m depth in the subsurface is used for water supply of the city of Freiburg im Breisgau. Within this area, slopes are flat (8 %) while the topographic gradient in the whole catchment is large (with topography ranging between 309 m a.sl. at the lowest point and 1480 m a.s.l. at the highest point) and steep hill slopes dominate in the mountainous part of the catchment (Wissmeier and Uhlenbrook, 2007). The length of the river network in the Dreisam valley is about 108 km.
The monitoring system in the Dreisam valley consists of 20 measurement stations located in the main tributaries and the main river (Dreisam) (Figure 3). At 11 locations, the water level is measured with both, the QR and Ody method. Each measurement is representative for a longitudinal section of the stream reach downstream of the measurement

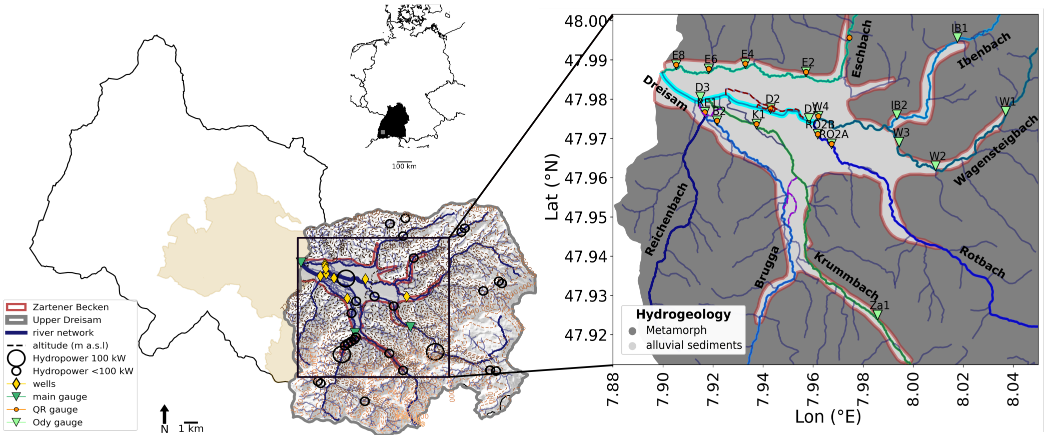

FIGURE 3 Overview of the extent of the Dreisam catchment in South Western Germany, the upper part of the Dreisam catchment and the monitoring system in the Dreisam valley (Zartener Becken)

location until the next station or the mouth into the main river. The choice of measurement locations was made according to their distance to the mouth of the river reach into the main river and in order to account for different settings with different environmental conditions. In all of the important stream reaches, water level loggers were installed at least at one location close to the mouth of the stream reaches into the main river and at one location upstream close to the alluvial aquifer borders. If an official gauging station was present upstream (such as at the Rotbach tributary or in the Brugga tributary), no additional station was installed upstream.

The drying events from observations and public media in specific river sections during the previous years was considered for the choice of the locations. The image-based method with QR-code panels was only used in locations where the panels could be deployed on a vertical surface. These were either large rocks or bridges, weirs or small hydroelectric power plants. Settings differ with regard to light conditions and shape or size of the river sections. In order to investigate the effect of light reflections on the output of the image-based method, some of the cameras were placed below bridges. Furthermore, care was taken that the panel position was vertical and, that the distance between the panel and the camera was adequate to maintain the necessary image resolution. The position of the camera was adjusted as such that the panel was portrayed in the center of the image. However, due to the manual maintenance of the cameras and the influence of the natural environment, it was not guaranteed that the position remained exactly the same during the whole measurement time span. At each measurement location additional staff gauges were installed. Water levels are logged by Ody and QR WLL with a temporal resolution of 15 min.

4 | RESULTS

4.1 | Comparison of the measured water levels

Both WLL methods are firstly compared with regard to their application and operability through a comparison of the operational time, time and effort for installation and processing of the data. The Ody data was processed with the Odyssey Software (Ltd, 2012). Processing of the QR images took significantly longer than reading of the Ody data. It is not possible to obtain the exact duration for reading one image with QR because the number of QR codes detected per image varies according to water level and error sources. For example, reading of 100 images took 1.57 min with an Core i7 processor. The effort for the installation was comparable for both methods. Overall, the maintenance cost for the image-based method was greater. On the one hand, this is due to the energy consumption of the camera at this resolution. A battery with an electric charge of 4.5 A h was sufficient to keep the cameras running for approximately 1 month in winter and 2 months in summer on average. According to the manufacturer of the Ody loggers, the battery life is $>$ 9 months. Thus, battery replacement and data collection needs to be done at higher frequency for the QR method. On the other hand, the maintenance cost and effort for the QR measurements was high due to manual verification of the image section, the manual data collection and regular replacement of the memory cards. A possibility to reduce maintenance cost for both methods is to use cameras or data loggers with automatic data transmission to simplify data collection and troubleshooting and to improve the measurement setup for long term operation (which would in turn require more financial resources). Secondly, the data sets obtained with the different measurement methods can be compared with regard to data availability and completeness of the time series, data quality and consistency of the measured water levels. The data measured by the monitoring system was processed for the time period between June and October 2020. The density distribution of all water levels measured during the study period at each station separately for each of the measurement methods vary (Figure 4). The shape of the distribution differs depending on the measurement method used for some locations (e.g. K1, RE1, E4). The violin plots indicate that low water levels occur at higher frequency in the Odyssey data set, where the shape of the violin of the Odyssey and QR code data are alike (E8, E6), except for B2 and RO2B. In general, there are more outliers towards high water levels in the QR code data set. Overall, the violin plots underline that the hydrological dynamics may vary depending on the river reach and location. Whereas the violin plot of some locations is multimodal or bimodal (K1,

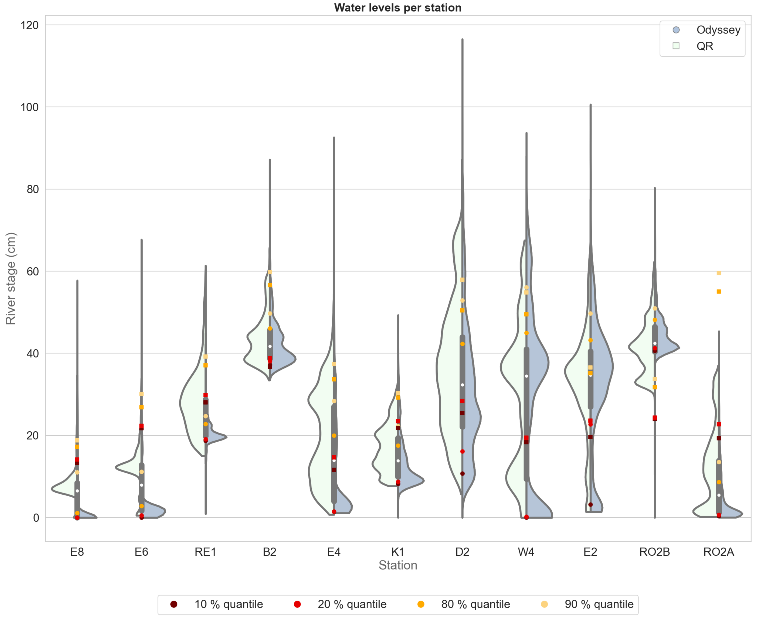

FIGURE 4 Violin plots showing the distribution of all measured water levels per station for both measurement methods. From left to right, the distance from the measurement location to the main gauging station near the catchment outlet is increasing.

W4, B2, E4, E2), the distribution is unimodal for other locations (E6,E8).

The percentage of available data per station is considerably lower for the QR data in comparison to the Ody data

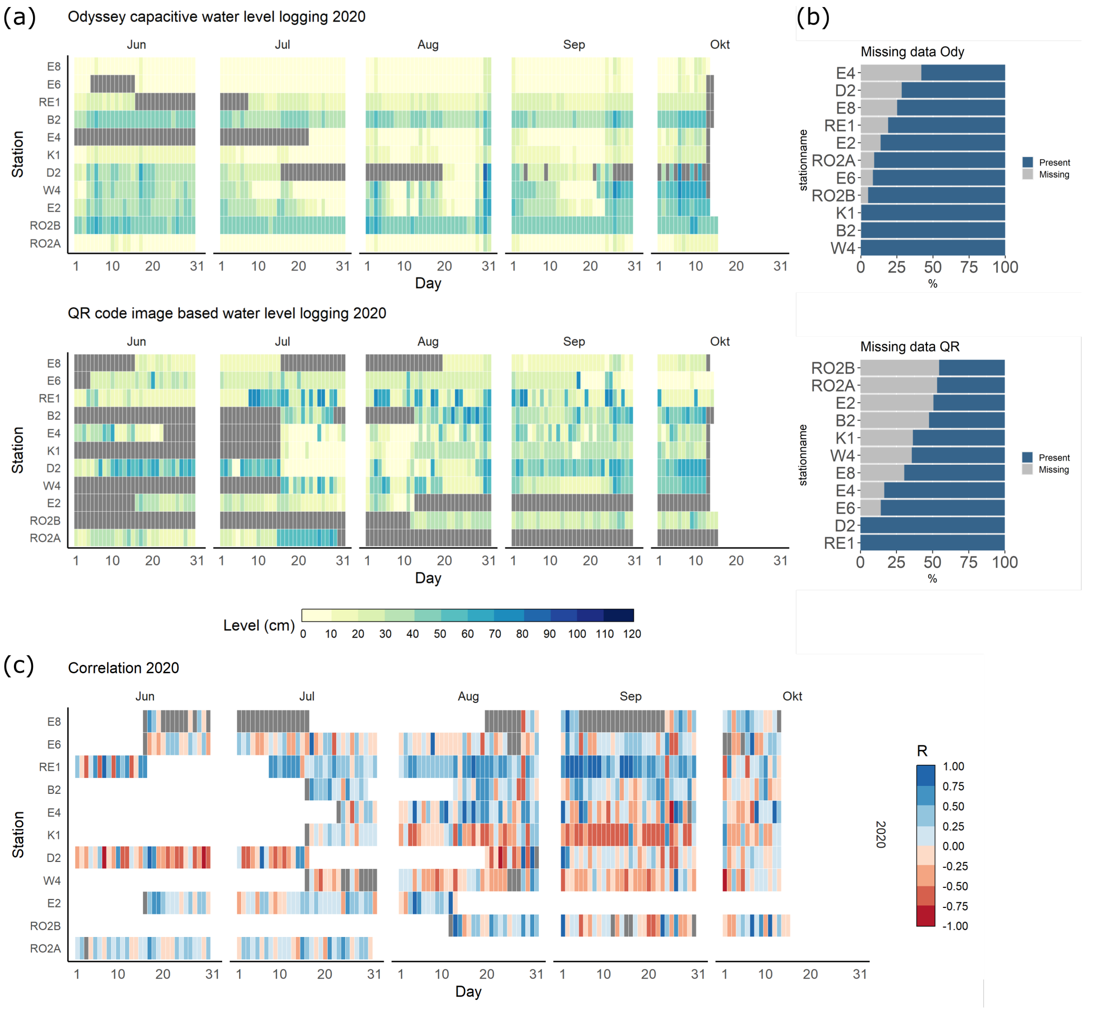

FIGURE 5 Data availability and rolling R for Ody and QR water levels. a) The range of water levels measured with each of the methods. b) Percentage of available data per method and measurement station. c) The rolling R (ranked pearson) for both measurement methods.

(Figure 5 b). More than 50 % of data was missing at some locations (i.e. at RO2A, RO2B and E2. Additionally, the temporal evolution of the water levels (15 min resolution) between June and October 2020 at each measurement location is analysed (Figure 5 a). While the water level remains constant at some locations during the measurement period (i.e. constantly high water levels at RO2B and constantly low water levels at E6 and E8), other locations show stronger fluctuations and in some cases also a stronger tendency for low water levels to occur in the summer months (i.e. D2, E2, W4). Furthermore, the range of water levels measured with the Odyssey method suggests that the closer the stations are to the main gauging station in Ebnet (which is located in the valley bottom at the western edge and near the outlet of the catchment), the lower are the water levels in general. The further away the measurement locations are from the catchment outlet, the stronger are the fluctuations. With regard to the distance from the catchment outlet of the gauging station, the QR code measured water levels do not show any clear differences. In general, fast changes from low to very high water levels occur more often in the QR water level time series (i.e. RE1).

Figure 5 c) shows, that there is no clear relation of Ody and QR measurements visible. Exceptions are RE1 and K1. At RE1, a relation of both measurements appears for most of the days. In some locations (i.e. K1) even a negative relation exists, meaning that the Ody water levels increase (decrease) while QR water levels decrease (increase). Note, that the Spearman's R can not be calculated for a standard deviation of 0, which is the case when zero water level occurs over longer time windows than a day (for example at E8, E6 and W4).

4.2 | Hydrographs

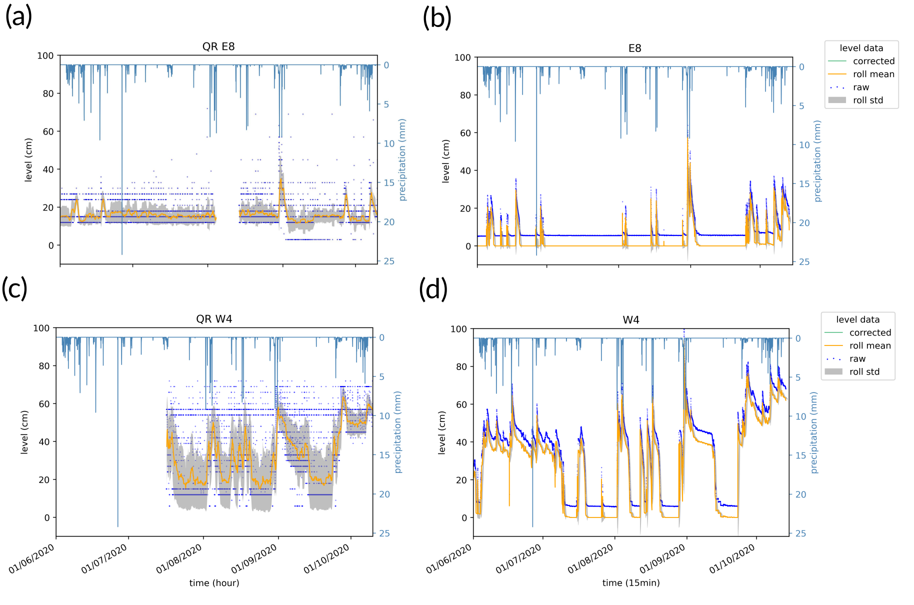

FIGURE 6 Hydrographs with 15 min water levels of QR (a, c) and Ody (b,d) measurements in summer 2020 at two measurement stations of the Wagensteigbach and Eschbach river reach and precipitation from the DWD. Raw data is displayed in blue, corrected data in green and the rolling mean of the corrected time series in orange. Standard deviation is shaded in grey.

The hydrographs (raw data in 15 min resolution without corrections) of the Ody and QR measurements show the different temporal dynamics at different locations along the stream reaches (Figure 6 (a-d) blue lines. More hydrographs are shown in the supplemental material Figure A.3 and A.4). Ody data was corrected using the mean of the minimum in the water level time series for all stations, where the minimum was below 5 cm (Figure 6 b and d green lines) (see section 2.3).

In the hydrographs for locations E8 in the Eschbach tributary and W4 in the Wagensteig tributary calculated with the Ody data, a time span with constantly (slope close to zero) very low water levels below 5 cm in the corrected time series (10 cm in uncorrected time series) appears several times in between the peaks during the study period (Figure6 b and d). Water level rise often occurs shortly after rainfall events, as expected due to the fast reacting character of the hydrological system (Wissmeier and Uhlenbrook, 2007; Uhlenbrook, 1999). The QR hydrographs reflect the same general pattern as the Ody hydrographs but with more outliers towards higher water levels. Longer time spans with constantly low water levels are not visible in the QR hydrographs. Instead smaller, high frequency fluctuations occur in between the marked peaks while water levels rarely drop below 10 cm (Figure6 a and c). The spread in the rolling STD (shaded in grey in Figure 6) is also noticeably smaller for the water levels measured with the Ody method (water levels are less scattered), regardless of the temporal resolution (15 min, hourly or daily). All in all, the hydrographs show, that water levels measured via QR tend to be overestimated in comparison to the Ody data (despite QR measurements being limited to 73 cm), similar to what the range of water levels in Figure 5 and 4 indicates.

The different results of Ody and QR code measurements can be explained by looking at different error sources that are typical for image-based measurements of water levels. After visual inspection of the images in our data set, we identified sediment accumulation on the panel, light reflections and overexposure as the major error sources (supplemental Material Figure A.1). Overexposure occurs in locations, where the angle between QR code panel and the sun is particularly unfavorable at a certain time during the day. This effect of back radiation is probably enhanced by the predominantly white panel background. Light reflections are mostly caused in places, where the interaction of sun light and leaves of trees or other plants create a pattern of light and shadow on the panel. Sediment accumulation is caused by the deposit of organic material on the panel at and below the water surface. When the river bed dries, the deposits dry, remain on the panel and conceal a part of the QR codes. The three error types are caused by the local environment. We therefore focused on errors due to local environment for pre-and post processing of the images (see section 2.2).

4.3 | Zero level occurrences

With the Ody data set we conducted an analysis of zero level occurrences for all stations. Zero level events were selected from the Ody data based on a threshold value and a rolling coefficient of variation (see also section 2.3). In Figure 7 a) and 7 b), the hydrographs, the threshold and the selected zero level occurrences in the time series are highlighted in red are shown for the two locations with different dynamics at the Eschbach tributary (E8) and the Wagensteig tributary (W4) (see also Figure 3). E8 represents an example with particularly long dry phases, whereas the status is alternating between dry and wet phases with higher frequencies at W4. As time lapse cameras and Ody loggers were closely installed and the river bed and loggers are on the images in most cases, it was assumed that the images from the time lapse cameras can be used for validation of the zero level occurrences (see chapter 2.2. However, due to the high temporal resolution of 15 min, the visual inspection of images at locations where the riverbed is prone to run dry frequently and for several days requires tremendous time and effort. For E8, this would have required to visually inspect 8323 images. Therefore, a random choice of 10 % of the images were validated. Of the 10 % of the images, the riverbed was classified as dry for 92 % of the images at E8 and for 100 % of the images at W4 . This illustrates, that the selection of zero level occurrences for the two measurement locations was correct. The same methodology was applied for all other locations in the catchment (see Figure A.6 in the supplemental material. All locations with Ody loggers are included as shown in Figure 3).

Hence, an analysis and intercomparison of the total zero level occurrences per month of the different locations for the measurement period between June and October 2020 is feasible. An overview of the monthly percentage of

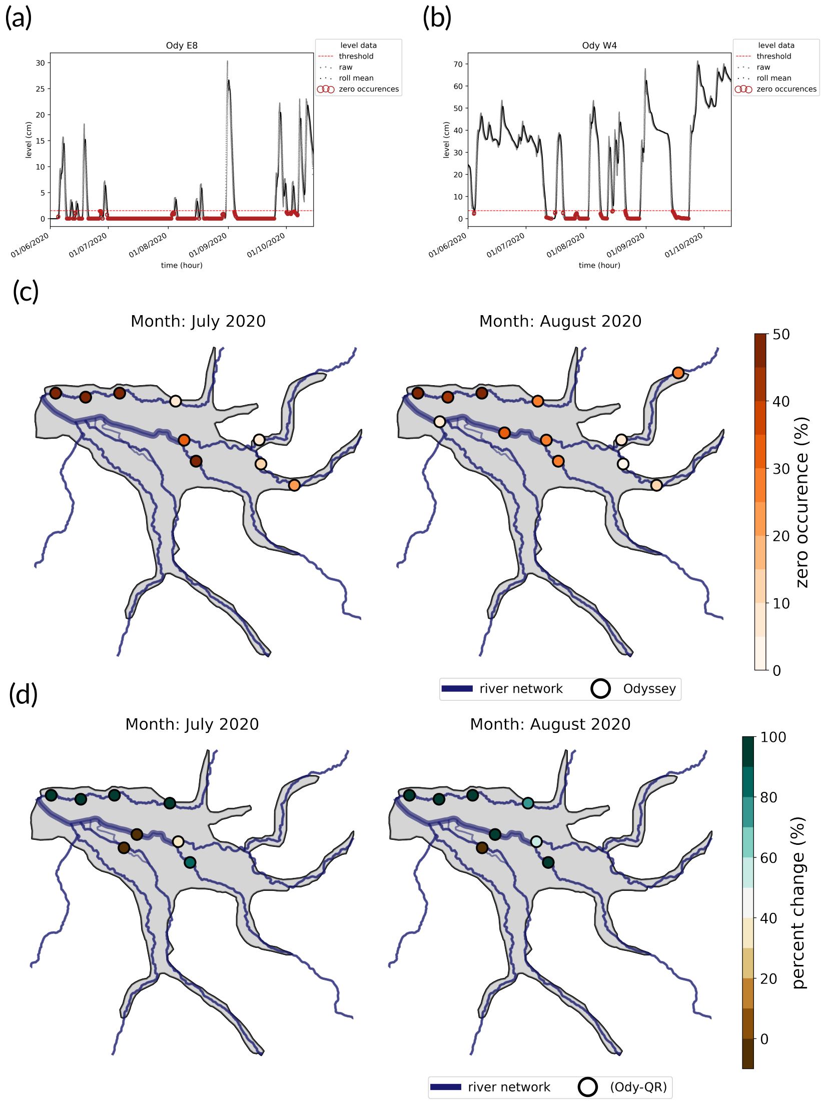

FIGURE 7 a, b) The zero level occurences selected from the data set for two of the measurement locations for the locations E8 at the Eschbach tributary and for W4 at the Wagensteigbach tributary. c, d) Total monthly zero water level occurences per measurement location in percent for the Ody data and percentage change between zero occurences obtained with Ody and QR data.

zero occurrence between June and October 2020 is given in Table 3 for the Ody data set. The percentage of zero level occurrence is calculated based on the total number of values N that was measured at each location per month. Zero water levels occur at first in June 2020 and throughout July and August the severity of the hydrological drought increases and a dry riverbed is measured at an increasing number of locations and over longer time periods (Figure

TABLE 3 Total Number of measured values (N) and percentage of zero level occurences per Month

Month 2020	May	Jun	Jul	Aug	Sept	Oct	May	Jun	Jul	Aug	Sept	Oct
stations			N						percentage (%)			
B2	529	2880	2976	2976	2880	1312	-	-	-	-	-	-
D1	0	0	826	2976	2880	1307	-	-	-	-	-	-
D2	533	2880	1591	2192	4931	1900	-	-	-	34,63	1,8	-
D3	0	0	0	1105	2880	1298	-	-	-	8,6	54,37	-
E2	577	2880	2976	2976	2880	1303	-	-	9,21	28,09	1,15	-
E4	0	0	1243	3913	2880	1301	-	-	56,56	48,38	-	-
E6	577	2880	2976	2976	2880	1298	-	23,3	57,49	42,88	18,75	-
E8	577	2880	2976	2976	2880	1296	-	36,28	100	67,54	65,69	30,86
IB1	261	3150	3255	3273	2900	1345	-	-	-	26,34	13,48	-
IB2	263	3150	4041	3812	2898	1345	-	-	7,52	7,92	-	-
K1	531	2881	2976	2976	2880	1310	-	-	-	-	-	-
RE1	231	1589	2254	2976	2880	1315	-	17,62	-	-	-	-
RO2A	375	3180	4074	4754	4338	2017	-	19,25	63,38	29,51	23,19	-
RO2B	371	3150	3255	4017	4320	2017	-	-	-	-	-	-
W1	267	3150	4042	3830	2900	1345	-	-	-	-	-	-
W2	522	6060	5454	4745	2971	1345	-	3,38	21,29	14,96	-	-
W3	264	3150	4059	4774	4339	2017	-	-	10,37	4,61	-	-
W4	341	2880	2976	2976	2880	1305	-	0,31	33,06	29,1	24,03	-
ZA1	235	2880	3911	4743	4338	2017	-	-	-	-	-	-

7 c)). E8 was dry for 100 % of the time in July, 67 % in August and 65 % in September (Figure 7 a)). In September, zero level occurrences start to decrease and most locations recover from the drying until October 2020, E8 being the only station where the riverbed is still partially dry. In general, this indicates, that especially the north western part of the study area appears to be most vulnerable (see also supplemental material Figure A.2). Additionally, a longitudinal drying pattern emerges along the Eschbach river, as downstream stations dry out at first and upstream stations start to be affected later in July and August (Figure 7 c)).

Nevertheless, streams in the central part of the catchment also show relatively high monthly percentage of zero levels from July to September. The least vulnerable to hydrological drought are the south western parts of the catchment. Additionally, the percentage change ($\frac{(x_{ody}-x_{qr})}{|xody|} * 100$) between Ody and QR zero level occurrences for the locations where data on both measurement methods exist was calculated (Figure7 d), see also supplemental material Figure A.5). At most locations, the percentage of zero levels measured with the Ody data surpasses the percentage of zero levels measured with the QR data in July and August. This is strongest for the Eschbach tributary, where the percentage change between Ody and QR zero occurrences is > 90 %. Exceptions are the locations K1 and B2, were the evaluation of QR records indicates more zero level occurrences.

5 | DISCUSSION

5.1 | Technical challenges of QR code based WLL

In this this study we present a first attempt to measure with the QR WLL method in a natural environment with very basic equipment and therefore measurement errors arise in part from the measurement setup. Different error sources of QR WLL lead to higher measurement inaccuracy and especially to overestimation of low water levels in comparison to the Ody WLL method. Any future application of QR WLL should therefore have to entail an improvement of the measurement setup. Firstly, the accuracy of the QR WLL is limited to (3 cm) due to the size and arrangement of the QR codes on the panel. This resolution is not sufficient for water level measurements according to the guidelines of the federal state of Baden Württemberg (LAWA, 2018) and to develop rating curves. In general, the resolution is dependent on the quality of the camera or image, the size of and the distance between the QR codes. In this study, a key aspect was to find a low-cost solution. It is therefore expected, that the resolution problem could be enhanced using smaller QR-codes and better photographic equipment (i.e. higher image resolution). Hence, the error sources that were identified with our measurements in a natural environment (see supplemental material Figure A.1) indicate, that the measurement technology requires further refinement to be directly applied in the field. This calls for testing of varying technical setups in laboratory environment in order to find out at what smallest possible resolution the approach still deliver valuable results. Different coatings could be tested to solve problems with sediment accumulation on the panel and for different light conditions and illumination. Problems with over exposure and light conditions may also be avoidable if the geographical orientation of the measurement location is taken into account (a North oriented panel is likely not as much affected by sunlight as a South, West or East oriented panel).

We have also shown that a distinction between different error sources by means of simple, automatic image-processing techniques is not yet possible (Figure 2) and therefore cannot compensate for refinement of the experimental design to avoid the above-mentioned problems. Concurrently, image-processing techniques also still need to be improved to reliably filter erroneous images in a pre- or post-treatment.

Despite deliberate maintenance, several data gaps appear in our QR dataset (Figure 5). For long-term monitoring, automatic data transmission is needed in order to reduce maintenance cost and to avoid deficiency of the devices for longer time periods. However, problems related to the energy consumption of self-made automatic data loggers based on Raspberry PI systems need to be solved first. For example, (Eltner et al., 2018) used a car battery to obtain data with 30 min to 1 h resolution. Furthermore, data transmission with such data loggers only works in areas with mobile coverage and such sensors may be sensitive to temperature as well, as it was shown by Elias et al. (2020) in combination with smartphone cameras.

5.2 | Measurement comparison

The quality and the amount of the data obtained with the QR method is lower while the data handling is also more complicated in comparison to the data obtained with capacitive water level logging. We therefore assumed that the data obtained with the Odyssey loggers is more reliable for an analysis of zero levels. Specific for the measurement of zero water levels, the combination of the general error sources when using image based measurements and the use of QR codes as fiducial marker lead to an overestimation of low water levels. This should be kept in mind when developing such image based methods using fiducial markers further also for applications like citizen science.

While the use of QR may reduce uncertainty due to subjectivity when interpreting the information on stage height contained in images visually, the flow status cannot be measured directly without making the assumption that the presence of water automatically indicates flow as well (at least not using an automatic algorithm). Thus, this is one of the shortcomings of the Ody method with respect to application in the context of IRES. Therefore it is essential to contrast the Ody with other measurement methods. Those could also be electrical resistance measurements, which have also been successfully used for monitoring (particularly for status changes) of IRES (Assendelft and van Meerveld, 2019; Bhamjee et al., 2016; Blasch et al., 2002) , ultrasound and radar technologies, which are also commonly used in hydrometry (LAWA, 2018) or even image-based if the information on flow status is assigned manually (Kaplan et al., 2020, 2019).

Furthermore, the correlation analysis revealed a contradictory behavior of QR and Ody measurement, which impeded complementary usage/merging of the two data sets. Nevertheless, the combination of the logged water levels and the visual data contained in the images from the QR-codes provides several advantages. On the one hand, it allows to counter check for external confounding factors in the river bed or the local environment that may influence measurements. On the other hand, the information contained in the image was useful for validation of the Ody measurements. Another advantage arises from the potential for examination of the time lag between different measurements.

A huge effort for image processing is necessary in comparison to the capacitive water level measurement. The quality of the result is dependent on image processing software used and requires advanced image processing methods to solve specific problems. Software was often developed for medical purposes and measurements under stable (laboratory) conditions (e.g. Kaplan et al. (2019) used the open source software ImageJ (Schneider et al., 2012)). There is potential in using image based measurements for hydrological purposes if new image processing techniques and machine learning algorithms (neural networks) are further developed in order to identify specific patterns and to deal with natural conditions for hydrological purposes (Eltner et al., 2021; Ljubičić et al., 2021). Convolution neural networks have shown to be more robust to environmental conditions but the findings of (Eltner et al., 2018, 2021) are in agreement with our findings, that light conditions are amongst others a major error source. We presume that those error sources have now been well identified but the solutions from an image treatment or artificial intelligence perspective have not yet been solved. This implies that up to date, particular care should be taken with respect to the choice of measurement location when working with image-based technologies (particularly in environments with tree shading).

5.3 | Zero level occurences

Using the Ody dataset, it was possible to analyse the longitudinal drying pattern and to evaluate the occurrence of hydrological drought per month in different stream reaches in the Dreisam valley between June and October 2020 (Figure 7). Zero level or intermittency occurrence has often been validated using data from field mapping campaigns (Jensen et al., 2019; Zimmer and McGlynn, 2017; Shaw et al., 2017; Shaw, 2016; Godsey and Kirchner, 2014; Olson and Brouillette, 2006). Here, we successfully validated zero level occurrences based on the Ody data using images of the river bed. Hence, our results show that validation with image-based measurement methods is a promising alternative and helps to identify potential errors when filtering zero water levels. The validation of zero level occurrences also yields further potential for the application of deep learning techniques to identify zero water levels from the images. Under the assumption that zero water levels measured with the Ody loggers are also represented by the information contained in the images, the data sets could be used as training and validation data.

Altogether, the analysis of zero level occurrences denotes, that the obtained data set is suitable for an event based analysis of zero level events in our example catchment. In addition to the longitudinal drying patterns we were able to show that there are spatio-temporal differences of the occurrence of zero water level at different locations (Figure 7). However, a classification of the stream network into ephemeral, intermittent or perennial, data for the entire hydrological year is required on the one hand and streamflow data is necessary for further analysis of the spatio-temporal behavior of intermittent streams (for example in order to use active stream length vs. discharge relationships (Shaw et al., 2017; Zanetti et al., 2021) or to differentiate between different origins of hydrological flow (Zimmer and McGlynn, 2017)). For the measurement methods used in this study, rating curves (the relationship to calculate discharge as a function of recorded water levels) need to be developed to obtain discharge data. The generation of such rating curves could be a next step to estimate the contribution of each of the stream reaches to the main river and to quantify the amount of water that is missing once different stream reaches dry up. This is an essential step for the assessment of different control factors for the observed spatio-temporal patterns, especially in the context of an altered river system (with water abstraction and hydroelectric power generation).

6 | CONCLUSION

We evaluated the potential of an image-based measurement method using time lapse cameras and QR-codes as fiducial marker and a capacitive measurement method for measuring zero water levels based on the example of a meso-scale catchment with temperate climate in South Western Germany. We found, that the largest errors using image-based measurements were produced due to the local environment. Up to date, the available open source QR code readers are not able to distinguish between images affected by such error sources (i.e. light reflections due to patterns of light and shadow or due to the water surface and sediment accumulation) and a normal image. Where overexposure or sediment accumulation occurs, the information on the fiducial marker is lost leading to wrong measurement results. Therefore, image processing can only be used in order to exclude the erroneous images prior to reading the QR codes with a software. We experienced, however, that a simple algorithm for automatic thresholding is not sufficient in order to account for error sources due to the natural environment. Thereby, we conclude, that the choice of the measurement location is extremely important when working with image-based methods, especially if stream reaches are partially tree-shaded. Due to the above mentioned error sources and the high efforts for maintenance and data handling, the data obtained with the image-based method could not be used alone for an analysis of zero level occurrences. A brief analysis of zero level occurrences using the data of the capacitive measurement method for the measurement period between spring and autumn 2020 showed, that the use of image-based data can be rewarding in order to validate the results. As long as there are no specific solutions for image-processing available, there is potential to use image-based measurement methods in combination with other measurement methods in order to reduce measurement uncertainty.

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conflict of interest

The authors declare no conflict of interest.

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GRAPHICAL ABSTRACT

Measuring zero water level in stream reaches: A comparison of an image-based versus a conventional method

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