The UWO dataset – long-term data from a real-life field laboratory to better understand urban hydrology at small spatiotemporal scales

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Abstract. Although urban drainage systems are essential infrastructure, monitoring their functioning is cumbersome, hazardous and can be very expensive. This makes it difficult to track spatio-temporal dynamics of the fast hydrological processes. Also, openly available datasets from urban drainage systems are lacking, which makes it challenging to develop methods for automated data quality control. In this study, we present a unique dataset from the Urban Water Observatory (UWO) field lab in and around the municipality Fehraltorf, Switzerland. The dataset comprises coherent information from 124 data sources that observe rainfall-runoff processes, wastewater and in-sewer atmosphere temperatures. Of those 124, 89 sources transmit their signals via a specifically set-up wireless network using low-range low-power transmission technologies. Sensor data has a temporal resolution of 1-5 minutes and covers a period of three years from 2019-2021. To make the data interpretable and re-useable we provide systematically collected meta-data, data on sewer infrastructure, associated geoinformation including a hydrodynamic rainfall-runoff model. Basic data quality checks were performed, and we motivate future research on the dataset with five selected research opportunities from detecting anomalies in the data to assessing groundwater infiltration and the capability of the low-power data transmission. To obtain interpretable and reusable urban drainage data, robust automated data quality checks, and standardized exchange formats are needed. In the future, using ontologies and knowledge graphs could be developed to expand the application of sewer observation data in solving scientific and practical problems.

1 Introduction

Urban drainage systems are essential for public health and sanitation (Ferriman, 2007), because they not only safely transport wastewater and reduce the risk of waterborne diseases, but also protect groundwater and prevent flooding in populated areas. Thus, a profound understanding of the urban hydrological processes is crucial to develop urban areas to more liveable, more sustainable cities. Innovation in this field comes from first principles and data (Eggimann et al., 2017; Blumensaat et al., 2019). However, collecting data in urban hydrology is expensive, because sewers are a hazardous environment that requires specialized training and equipment (Nedergaard Pedersen et al., 2021). Although sharing datasets among research groups has always happened on a personal or project basis (Deletic et al., 2011; Lepot et al., 2016; Caradot et al., 2013; Ochoa-Rodriguez et al., 2015), it is not well established, neither in the research community nor among practitioners.

Understanding urban hydrological processes require high-resolution data on both, the input - such as rainfall - and the output - such as wastewater flows and pollution. However, reliably collecting minute-by-minute rainfall data over many years can be challenging (Bianchi et al., 2013); monitoring stormwater runoff, wastewater flows and pollution processes at a minute scale is resource-consuming. Specialized equipment, training, and software (Mourad and Bertrand-Krajewski, 2002; Dürrenmatt et al., 2013) as well as considerable investments are required to collect and manage the data, as well as to maintain the sensors (Hoppe et al., 2016; Blumensaat et al., 2019). Arguably, sensor maintenance to ensure good data quality is one of the biggest challenges in urban monitoring (Mourad and Bertrand-Krajewski, 2002; Nedergaard Pedersen et al., 2021). Data quality is often dubious due to the low data literacy of the sewer workforce and lack of incentives to use data for evidence-based management of urban drainage systems (Manny et al., 2021). In addition, the lack of standards and meta-data makes it difficult to work with existing or historical data.

To address these issues, there is a need to provide examples of open datasets (Nedergaard Pedersen et al., 2021), which can be used to develop procedures for data quality management and better understand the highly dynamic processes of rainfall-runoff and water quality. Unfortunately, the urban drainage research community has not yet fully embraced Open Science principles and openly available datasets of rainfall, runoff and water quality, as well as topological data of the urban drainage network and a domain-specific description of the catchment, i.e. including land use data and terrain models, are virtually lacking (Nedergaard Pedersen et al., 2021).

Recently, four main factors drive the need for open datasets in the field of urban hydrology. First, advancements in low-power electronics, data transmission (Ebi et al., 2019) and sensor application (Mathis et al., 2022; Boebel et al., 2023) have significantly reduced the effort of data collection. Second, meta-data efforts and OGC-standards have facilitated data sharing among researchers and practitioners (Taylor et al., 2013; Bustamante et al., 2021). Third, scientific data collection efforts, such as the data set “Catchment Attributes and Meteorology for Large-sample Studies (CAMELS)” (Newman et al., 2015; Addor et al., 2017), have truly revolutionized the field of hydrology through the use of advanced data-driven models (Kratzert et al., 2018). Fourth, the public demands greater transparency of urban infrastructure performance, including reducing environmental pollution (Benyon, 2013; Giakoumis and Voulvoulis, 2023). In this regard, sharing data from urban water management and making it available to the public will become increasingly important soon given the impact of climate change. Therefore, regulatory bodies, such as those in the UK (Environment Act, 2021) and in the EU (EC, 2022), are and will be demanding more monitoring, further emphasizing the importance of data collection and sharing.

Recently, some openly available datasets have been highlighted, some of which are just available for visual exploration (Spraakman, 2023). For other available datasets[1], no historical data are available. One promising example is the Bellinge dataset from Denmark (Nedergaard Pedersen et al., 2021), which includes rainfall runoff data from 17 level sensors on the hydraulic behavior of the systems, such as levels, pump power and flows and 3 rain gauges, as well as X-band and C-band radar and air temperature. It is particularly strong on the asset data, which even includes CCTV footage and two different hydrodynamic models. Unfortunately, given the complexity of the system, it only provides data from comparably few sensors and limited meta-data on sensors: "[…] *exact documentation of sensor maintenance has not been a high priority over all the years, and it is therefore presently not possible to give an overview of when and where sensors have been repaired, been replaced or received some sort of maintenance.*" (Nedergaard Pedersen et al., 2021, p.4786). Thus, important sensor-related meta-data, as well as information on wastewater and stormwater quality is missing.

In this publication, we present curated data from the Urban Water Observatory (UWO) field lab in and around the municipality Fehraltorf, Switzerland. The UWO dataset is unique due to its high spatial and temporal resolution, dense network coverage, and rich meta-data. It consists of four main data packages (A1-A4) (Figure 1), accompanying information (package B) and tools to explore and access the data (C and D). Specifically, the data packages contain 14 sources of precipitation and other meteorological variables (A1), 70 hydraulics sensors, e.g. flow, water level, overflow detection (A2), and 40 temperature measurements of wastewater and the sewer atmosphere (A3). Additionally, the dataset contains information on the behavior of 89 wireless sensor nodes (A4), partly from underground locations, which is unprecedented, to the best of our knowledge. The dataset has a temporal resolution of one to a few minutes and spans a period of three years from 2019-2021. It is complemented with detailed geoinformation including accompanying geographical and topological data as well as a hydrodynamic rainfall-runoff model implemented in SWMM (B). We also provide tools to visually explore the data (C) and example scripts to access the monitoring data (D). Most importantly, the data is rather complete with few periods of outages (cf. data completeness in Fig. 4, right), and it has a high level of consistency . Thus, the UWO dataset presents ample research opportunities from improving our understanding of urban drainage processes, to testing the accuracy of process-based as well as data-driven methods, and even assessing the performance of wireless sensor networks in underground applications.
In the following, we describe the catchment of Fehraltorf, the available sensors and datasets as well as the methods used to collect, process and explore the data. Finally, we highlight five exemplary research opportunities in the prospect of the UWO dataset (Figure 1).

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[1] https://www.kaggle.com/datasets/new-york-state/nys-combined-sewer-overflows-csos; https://theriverstrust.org/key-issues/sewage-in-rivers

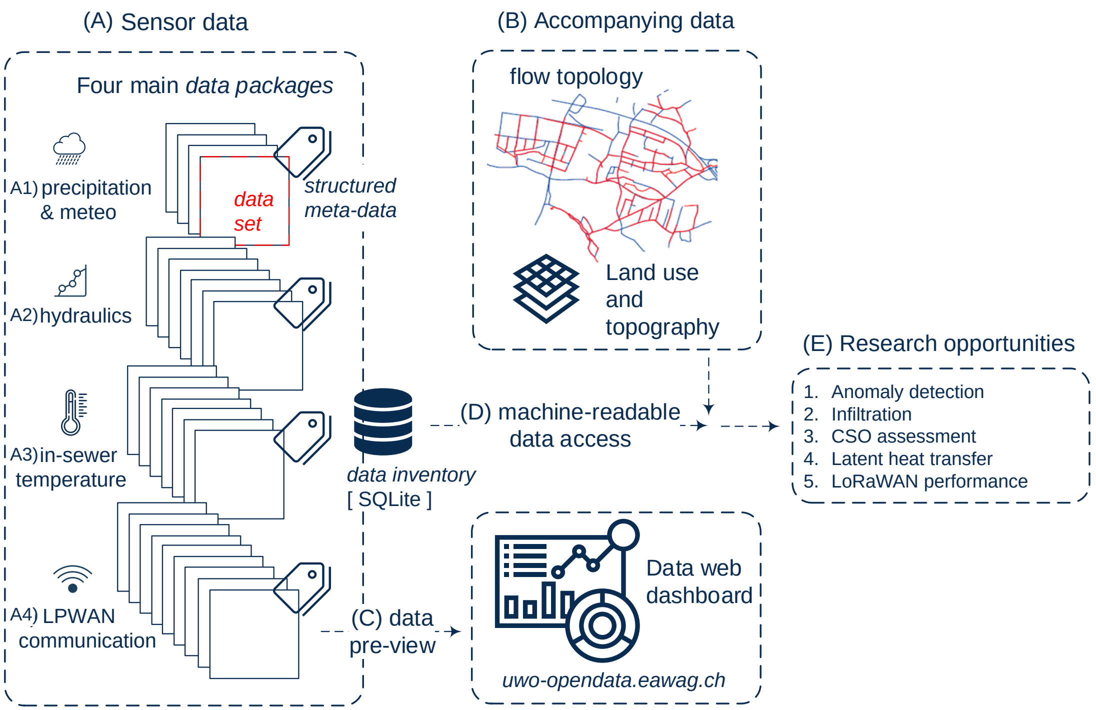

Figure 1: Graphical representation of data provided (A-B), the current webapp data viewer (C), scripts to access the data (D), and examples to highlight future research opportunities in the prospect of the UWO dataset (E).

2. Material

2.1 Description of the catchment

Fehraltorf is a municipality located in the vicinity of Zurich and Winterthur, at an elevation of 530masl with a population of 6,292 inhabitants in 2015 (HBT, 2016) and 6,578 in 2020. In terms of administrative boundaries the municipality covers an area of 950 hectares with over half of it being used for agriculture (52.7 %), 26.9 % being forested, 13.4 % being developed for settlements, and 5.7 % being designated for transportation purposes (as of 2007) (Figure 2).

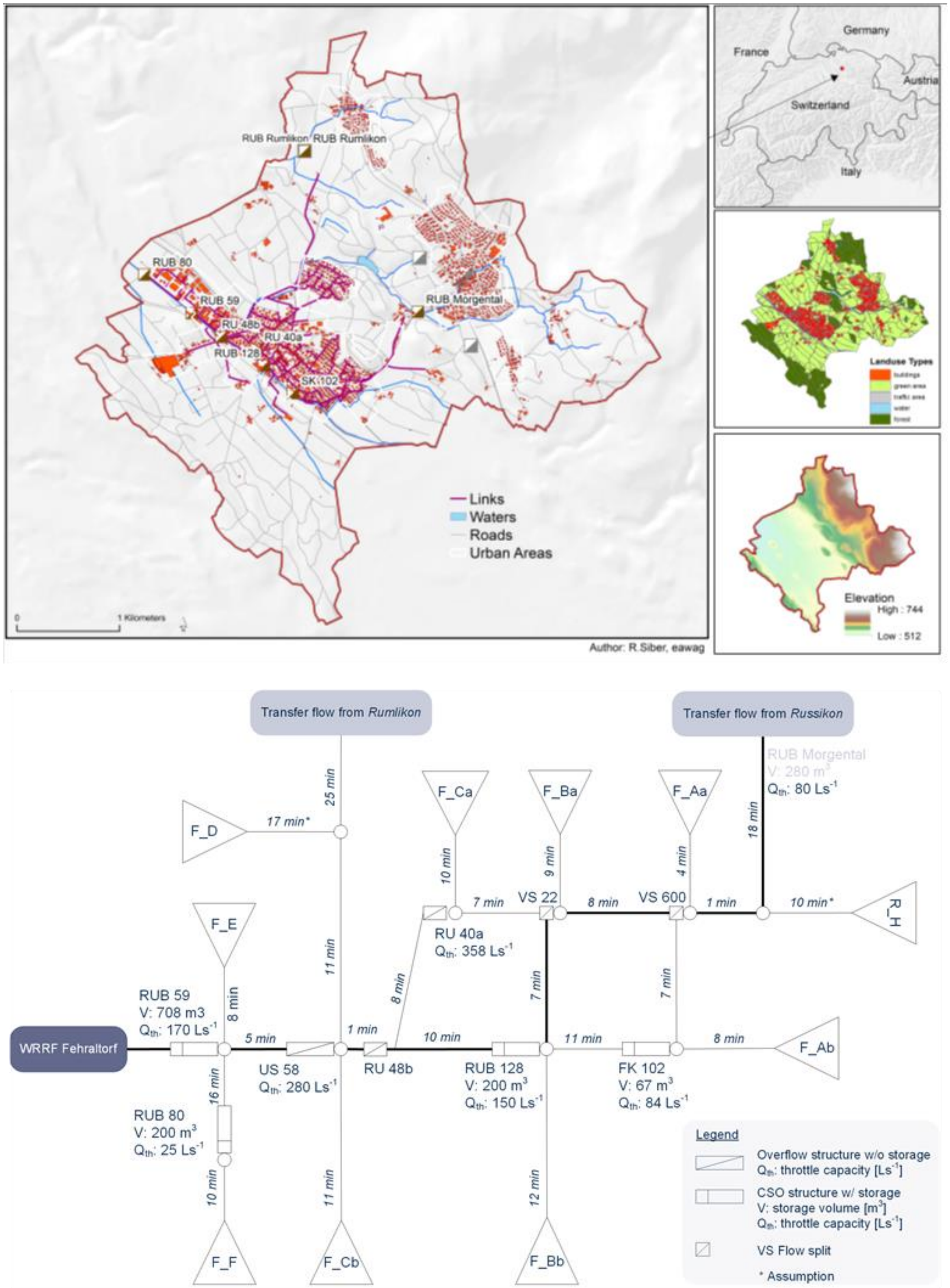

Figure 2, Top: Overview of the Fehraltorf catchment, including urban drainage network, geography and land use. Bottom: The urban drainage flow scheme of Fehraltorf, illustrating the combined sewer network of Fehraltorf. The main flow path through the network is from top right to the left (bold line). Triangles represent aggregated sub-catchments. The relevant characteristics can be found in the supporting information. The here indicated flow times are estimated assuming a flow velocity in the sewer of 1 ms $^{-1}$.

The climate in Fehraltorf is a typical humid continental climate,[2] with warm summers and cold winters. The average temperature in the warmest month is above 10 °C and the average temperature in the coldest month is just below -3 °C. The mean annual precipitation (1981-2010: 1334 mm) is distributed throughout the year, with an average rainfall depth in February of 78 mm and the heaviest amount falling in the summer months (ca. 140 mm) (see Supporting Information (SI) Section 1 for details). The climate region has a high variability in weather patterns and the frequency of storms and extreme weather events.

2.2 The urban wastewater system and the River Luppmen/Kempt

The drainage system of Fehraltorf is mostly a combined sewer system, which consists of 13 km of combined sewers, 4.6 km of foul sewage pipes, and 10.9 km of stormwater pipes. The municipality's runoff-efficient, i.e. reduced area is 40 hectares, as reported in the general drainage plan (HBT, 2016). The system has six overflow structures of which four have a notable retention volume; the area-specific storage volume is about 36 m^3 per hectare runoff-efficient area. Two additional flow split structures (VS22 and VS600) provide hydraulic relief within the system during large storm events, but do not spill into the environment (see Figure 2, where the bold line depicts the main flow path).

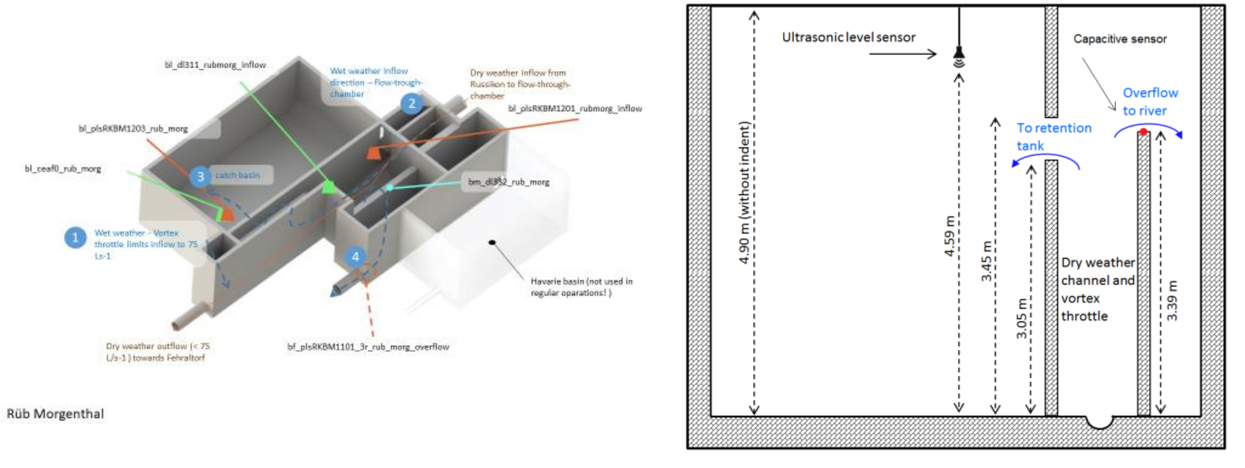

Figure 3 left, CAD model of the CSO tank "RUB Morgental" including inflow chamber, detention tank, overflow to receiving water and installed sensors. Right: Cross-section through the overflow structure at the sensor bl_plsRKBM1201_rubmorg_inflow (not drawn to scale). Detailed information of all detention basins and flow control structures is provided in the SI.

[2] According to the Köppen-Geiger climate classification, the climate in Fehraltorf is classified *Dfb* (*cf.* https://skybrary.aero/airports/lszk - last access 23.04.2023)

The nearby villages of Russikon (3320 inhabitants) and Rumlikon (451 inhabitants) are also largely connected to Fehraltorf's wastewater treatment plant (WWTP) (HBT, 2016) (Figure 2). Also included in the dataset is the RUB Morgental (Figure 3), the catchment-concluding CSO structure in Russikon that limits the transfer flow to 75 Ls-1 towards Fehraltorf.
A significant portion of the drainage network infrastructure is located below the average groundwater table. Thus, some parts of the network are affected by sewer infiltration. Depending on the season infiltrating groundwater contributes to the WWTP inflow; the contribution varies from 35% up to 55% (HBT, 2016). The overall performance of the sewer system has been evaluated as satisfactory by the consultant engineers Hunziker Betatech (HBT, 2016). More details on the drainage system and the special structures is given in Sections 2 and 3 of the SI.

The Fehraltorf WWTP is a modern facility that removes solids, organic pollutants as well as nitrogen from wastewater through various stages of physical treatment and activated sludge processes. The facility has a maximum hydraulic capacity of 170 Ls^{-1} and contributes a major share to main water course, the River Luppmen. As there is considerable industry and commerce in Fehraltorf, e.g. chemical, paint, metal, pharmaceutical and others, the WWTP is substantially influenced by industrial emissions (AWEL, 2021). It is currently being upgraded to eliminate micropollutants with adsorption to powdered activated carbon.

The River Luppmen is the main water course which flows through Fehraltorf, where it changes its name to Kempt at the junction with the Wildbach tributary. The ecomorphology of the Luppmen is heavily influenced by human activity and is partly described as artificial (HBT, 2016). The minimum residual flow (Q_{347}) in the Luppmen amounts to 46 Ls^{-1} upstream and 72 Ls^{-1} downstream of Fehraltorf (HBT, 2016), which means that the proportion of treated wastewater can be greater than the natural baseflow of the river, especially in dry summer periods.
The intensive use of groundwater in the last 30-40 years has led to a continuous lowering of the groundwater level and, as a result, to a reduction of groundwater discharge into the Luppmen in the residential area of Fehraltorf. During prolonged periods of dry weather, stretches upstream of the confluent with the Wildbach dry out completely (Krejci et al., 1994).

In 2015 Fehraltorf was chosen as the location for Eawag's Urban Water Observatory (UWO), because the prior knowledge on the urban wastewater system (Krejci et al., 1994), its proximity to Eawag, and its similarity in size and system characteristics to many settlements on the Swiss Plateau. Monitoring started in May 2016, reached a peak in 2022 with 124 sensors. Today, the UWO is still operated with a reduced number of sensors.

2.4 Sensor data

The provided dataset consists of data collected from 2019 until 2021. This time window was chosen since collected data are most complete and show a consistent level of adequate data quality. It contains sensor signals with a high temporal resolution of typically 1-5 minutes on precipitation and meteorology (Figure 2, A1), wastewater hydraulics (A2), temperature of the wastewater and the sewer atmosphere (A3) and measurements of the performance of the data transmission (A4), i.e. the LoRaWAN[3] network. We define a data source as a combination of sensor and logger, which means that a source, e.g. a rain gauge, can transmit several signals, e.g. instantaneous precipitation, accumulated volumes or battery voltage. The provided sources not only include our own instruments, but also selected sensors of the utility's SCADA System. Therefore, the data were collected automatically from various sources such as FTP servers, databases, and platforms of manufacturers (see Section 3.1). In addition to the measurement data, important meta-data, such as logbook entries, e.g. on maintenance or operational malfunction, or detailed pictures of the installation, complete the data set (see SI Section 4). In absence of established standards, we developed a specific naming convention, according to the structuring principles of the norm on industrial monitoring EN 81346 (IEC 81346-2, 2019) as described in the SI in Section 5.

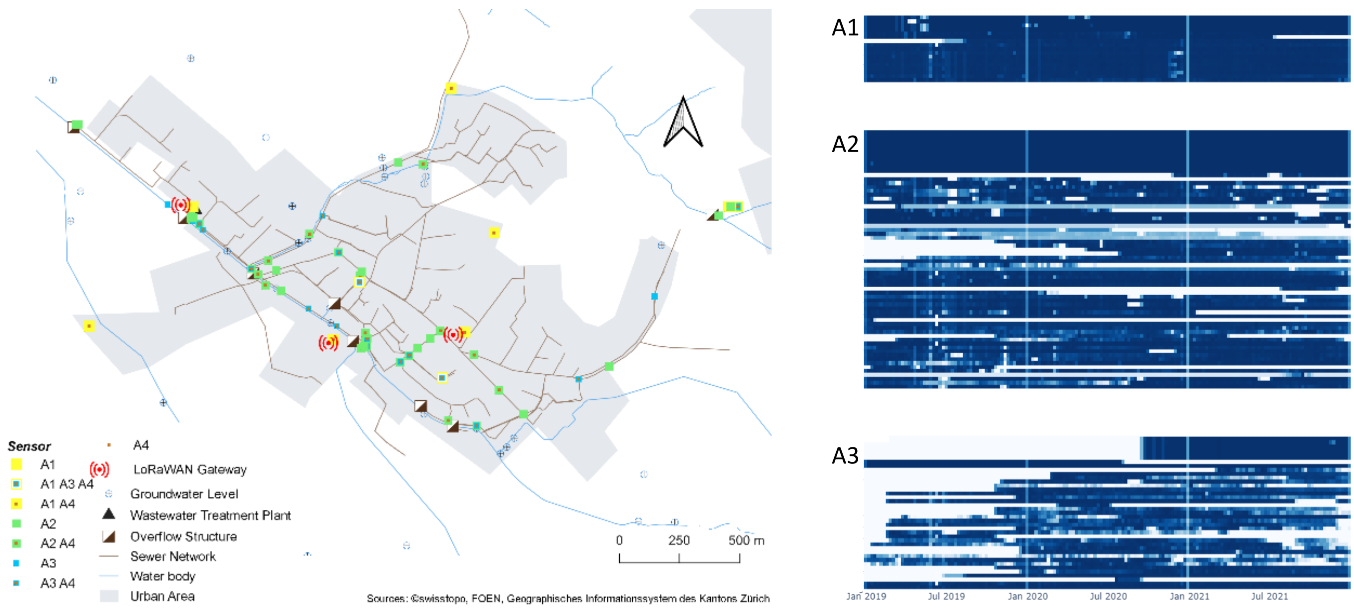

Figure 4, Left: Locations of sensors and sensor nodes. Right: Data completeness from 01.01.2019 to 31.12.2021. A1= precipitation sensors, A2= hydraulics sensors, A3= temperature data. A4 (LPWAN sensor nodes) is not shown. The color saturation indicates the degree of data completeness on a weekly basis. Dark blue indicates periods with 100 % data completeness , i.e. all data points are collected according to the sensor node configuration; white indicates periods with no data. Light blue indicates a reduced number of data points, either through sensor maintenance, sensor outage or incomplete transmission. We provide a dynamic plot in package C, which can be used to interactively explore the data availability and view details. See SI Section 6 for details.

[3] LoRa, ("Long Range") represents a proprietary radio communication technique, whereas LoRaWAN "Wide Area Network") delineates the communication protocol and system structure. LoRaWAN has gained recognition as an official standard, ITU-T Y.4480, within the International Telecommunication Union (ITU).

Table 1: Overview of the installed sensor types and some important characteristics.

		A1 - Precipitation and further meterological variables									
Brand	Ott	RM Young	Davis	Lufft							
Model	Pluvio2L	52202	Rain Gauge	WS700							
Number of sources	4	7	1	2							
Temporal resolution [min]	1	1	1	1							
Data transmission	Cellular	LoRaWAN	LoRaWAN	Cellular							
		A2 - Hydraulic measurements									
Brand	Decagon (Meter)	Decagon (Meter)	Decagon (Meter)	Hach	Keller	Maxbotix	Nivus	Nivus	Sommer	STS	PLS (SCADA)
Model	10 HS	5TM	ECTM	Flo-Dar/AV9000	PR36XKY	MB7369/7389/7386	CSM	POA	SQ-3	DLN70	various
Number of sources	1	10	1	3	2	35	2	2	2	1	11
Temporal resolution [min]	5	5	5	5	5	5	5	5	5	5	1
Data transmission	LoRaWAN	LoRaWAN	LoRaWAN	Cellular	LoRaWAN	LoRaWAN	Cellular	Cellular	Cellular	Offline	SCADA system
		A3 - Temperature measurements									
Brand	Maxim Integrated	Sensirion	UIT GmbH	PLS (SCADA)							
Model	DS18B20	SHT 21/35	TSIC	various							
Number of sources	28	4	6	2							
Temporal resolution [min]	1	5	30	1							
Data transmission	LoRaWAN	LoRaWAN	Cellular	SCADA system							

2.4.1 Precipitation and further meteorological variables (A1)

We operated four weighting rain gauges (OTT Pluvio^{2}L, catch area = 400 cm^2), which transmit via Cellular network and seven tipping bucket rain gauges (7x RM Young 52202, catch area= 200 cm^2 and 1x Davis Rain Gauge, catch area= 200 cm^2), which transmit their data via LoRaWAN. To avoid vandalism, they were installed preferentially on utility property, e.g. pumping stations or the enclosure of CSO facilities, or on rooftops. In contrast to the data of the Bellinge dataset (Nedergaard Pedersen et al., 2021), these gauges are not part of the national network operated by MeteoSwiss[4] and their measurements have not been quality controlled a priori. Nevertheless, they operated reliably during the 3-year period and measured the data in 1 min intervals. The OTT Pluvios were checked twice per year. Thus, they provide a comparably complete picture of the variability of liquid precipitation. The Davis rain gauge was chosen deliberately as a low-cost rain gauge operated at the site RUB Morgenthal. The meteorological variables have been collected by two multi-parameter weather stations (LUFFT, WS700), which simultaneously measure air temperature, humidity, pressure, precipitation, solar radiation and wind. Verified climatological information from MeteoSwiss is available for the stations *Kloten* and *Fluntern*, which are 15 km (Northwest) and 14 km (West) away from Fehraltorf. However, retrieval of actual precipitation and weather radar data is restricted to research and educational purposes and are not included in this publication.

2.4.2 Hydraulic measurements (A2)

In the study area, a total of 70 sensors have been implemented that survey the hydraulic behaviour of the network during dry and wet weather (Figure 4, A2). These sensor nodes measure and transmit data on hydraulic conditions at a temporal resolution

[4] MeteoSwiss - Swiss Federal Office for Meteorology and Climatology

of one to five minutes. Among these sensors, 35 are equipped with ultrasonic level sensors (MB7369/7389/7386, Maxbotix). Flows are recorded with two correlation wedge sensors (NIVUS), and four non-contact radar flow meters (2x Sommer, 2x Flo-Dar, MarshMcBirney). Additionally, 12 di-electric conductivity sensors (Meter, formerly known as Decagon) were installed as combined sewer overflow detectors (see Section 4.3) which provide redundant information on sewer spills (Blumensaat et al., 2017).

The "backbone" of the rainfall/runoff monitoring consists of four high-quality weighting rain gauges (OTT Pluvio^{2}L) and four industry-grade flow monitors (Nivus POA, Flo-Dar, Sommer SQ-3), which were deployed at strategic locations in Fehraltorf (see Figure 4, left) to provide reliable information on the functioning of the collection system during dry and wet weather. Flow monitors serve as a crucial anchor due to their ability to enable rainfall/runoff analyses and assist with flow balancing. They also survey relevant upstream boundary conditions, i.e. wastewater inflows from upstream sub-catchments: a) WW inflow from the Rumlikon district in the Northern part (F02), and b) WW inflow from the municipality Russikon is connected at the Northeast (F03). At two further locations (F08, F12, [F07, F10]) – redundant at the same site – we observe flow dynamics within the drainage network.

Level sensors and threshold detectors were mainly used to complement the flow meters, e.g. in smaller sewers and to better describe the filling, spilling and emptying behaviour of CSO tanks. For example, all overflow structures had been instrumented with at least one level sensor (MaxBotix and PLS) inside the CSO tank and one capacitive sensor (Meter) installed on top of the weir crest to act as a binary spill detector (SI Section 4.4).

Calibration of the hydraulic sensors was carried out at least once a year, but rather on demand than based on a structured maintenance schedule. Mechanical cleaning of the sensors, as well as reference measurements and visual checks (e.g., for perpendicular alignment of the non-contact sensors) were carried out regularly, besides the routine maintenance work (e.g., changing batteries) (see further details in the SI Section 4). The utility operates a process monitoring at certain structures, namely water level in retention basins as well as two flow measurements (Venturi and inflow WWTP). In the basins themselves, tank levels were monitored redundantly, mainly using low-power ultrasonic sensors (MB 7369/7389/7386, MaxBotix).

Some of the sensors were specifically tailored to sensor- units (nodes) to enable long-range-wide-area-networks (LoRaWAN). We used an operating voltage of 5 V or less and a current consumption of a few milliamperes for sensors and radio modules, which simplified the implementation of intrinsically safe devices to protect against ignition protection in the (per-se) explosive sewer environment.

2.4.3 Temperature measurements (A3)

Temperature can be used as a natural tracer to provide information on hydraulics (Dürrenmatt et al., 2013), groundwater infiltration (Schilperoort et al., 2013; Panasiuk et al., 2022) and sediments (Regueiro-Picallo et al., 2023). Also, net-zero considerations require a detailed understanding of urban energy and heat fluxes e.g., for energy recovery with heat exchangers (Hadengue et al., 2021), or to validate wastewater heat exchange predictions (Figueroa et al., 2021). Therefore, the in-sewer temperature was monitored using dual sensors that simultaneously record the temperature of the wastewater stream and the corresponding sewer headspace. Above ground, the ambient air temperature has been monitored at four locations across the catchment. To characterise surface runoff during wet weather, three additional temperature sensors were installed in gully inlets. The positions of the individual monitors are shown in Figure 4, left. This experimental design generates a consistent long-term data set, enabling the analysis of temperature dynamics within a hydrological context. It allows for studying temperature variations across different compartments at network scale, considering various seasonal and loading conditions.

2.4.4. Wireless Sensor Network and Nodes (A4)

Nowadays, the Internet of Things (IoT) is flourishing, and its prospects are promising, although early implementations were hindered by high costs, a lack of standards and technological challenges (van Kranenburg and Bassi, 2012). However, with the emergence of long-range low-power technologies like LoRaWAN, Sigfox or NBIoT[5], implementing and operating wireless sensor networks, i.e. of such Low-Power Wide Area Networks (LPWANs) has become straight forward. The increasing availability and sophistication of these technologies has enabled data collection, also in the field of environmental engineering, at an – so far – unseen density and scale.

Data transmission based on the LoRa® technology (Semtech Corporation, 2015) was a key factor in the UWO monitoring initiative. The UWO sensor network comprises i) 89 LoRa-enabled sensor nodes, ii) 3 LoRaWAN base stations, or gateways, and iii) network management elements (Blumensaat et al., 2017; Ebi et al., 2019). Data is transmitted between local sensor nodes and base stations using low-power, sub-gigahertz wireless communications, primarily utilizing the LoRaWAN protocol. According to our experience, LoRaWAN enables two-way wireless communication between independent sensor nodes and base stations with a moderate range of up to 20 km (above ground, subject to line of sight and weather conditions). Underground, we find typical transmission ranges of 500 m, which can be substantially extended with our LoRa-based mesh technology (Ebi et al., 2019).

[5] Sigfox, LoRa, and NB-IoT are all types of low-power, wide-area network (LPWAN) technologies that are used in the Internet of Things (IoT) ecosystem. While LoRa and Sigfox are classified as non-cellular IoT technologies, NB-IoT is categorized as a cellular IoT technology.

As sensor nodes, we deployed 89 industrial-grade nodes (DL-MBX, Decentlab) as well as custom prototypes (based on Libelium Waspmote). The DL-MBX nodes are powered by two standard LR20 alkaline-manganese monozinc cells (1.5 V, 18,000 mAh) and achieve a battery life of 3-6 years when transmitting every 5 minutes. Our custom prototypes are powered by standard lithium-polymer batteries (3.7 V, 6,700 mAh) and reach a battery life of about 0.5 years (Blumensaat et al., 2017). To connect the radio modules and sensors, we used digital data communication. This prevented interferences and facilitated seamless integration with the nodes' microcontrollers. We deliberately chose to connect the sensors to the radio modules via sensor cables, sometimes of several meters, which made it possible to optimise positioning of i) the sensors regarding the flow and ii) the radio module with regard to connectivity to the gateway.

To transmit the data from the sensor nodes, we installed three standard gateways (Kerlink Wirnet Station 868). The gateways receive signals from the sensor nodes and transmit the data via cellular to a network server. As network manager (middleware), we use commercial services provided by LORIOT[6] (Switzerland). This software manages the communication channels and data rates of the sensor nodes, sorting and forwarding the data packets to our internal data server. Although these services are subject to charges, they are far less costly than those for data transmission via SIM based internet connectivity.

To assess suitable radio coverage, we carried out several signal strength tests. Consequently, our examinations revealed that deploying three outdoor gateways atop elevated buildings emerged as a financially viable and efficient solution, striking a balance to ensure adequate signal potency across the entirety of the urban catchment region. This area spans approximately 3 kilometers by 3 kilometers in extension.

However, it's important to note that signal strength is not a constant factor, and the performance of the network exhibits temporal and spatial variations, as detailed in Section 4.5. .

The data of the LoRaWAN network is automatically transmitted via a data pipeline to our in-house data server and, together with the signals from the other sources, subsequently stored in our "Datapool" data management system (see Section 3.1).

3 Methods

To collect and curate the data from a large sensor network it is important to establish a data pipeline that provides automated data transfer, automatically stores the sensor data, performs automated and semi-automated quality checks and provides the data in the correct format and aggregation for the required services (Figure 5).

[6] loriot.io

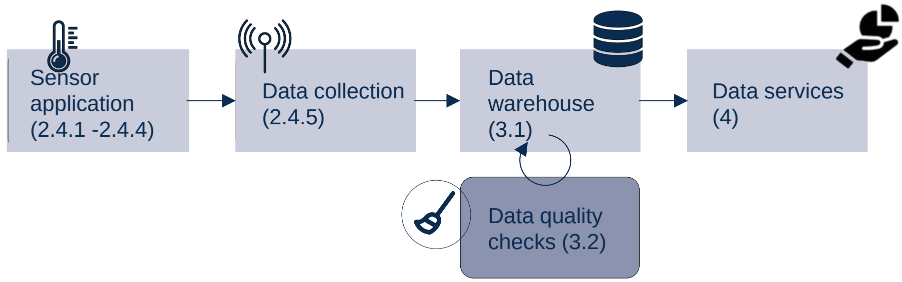

Figure 5: The individual components of the data pipeline for collecting, storing and using UWO open data from the sensor to the data service. The numbers refer to the corresponding sections.

3.1 Implementation of the data pipeline: Data collection, processing and storage

The "Datapool" is an advanced data warehouse developed at Eawag with implementation support by ETH Zurich's Scientific IT services. It utilizes open-source software, including PostgreSQL, PostGIS, TimeScaleDB, and a Python wrapper to manage structured data, such as time series, meta-data, signal quality information, binary data, raster data, and laboratory data. It allows for fast query processing, even with large amounts of data, and offers a clear separation of data management roles (see SI Section 5). The "Datapool" is based on open-source technology, allowing for high interoperability with other software. For simplicity, the approximately 120 GB of the UWO sensor data (packages A) have been split into three slices, one for each year, and exported in SQLite format.

3.2 Ensuring consistent data quality

Long-term field monitoring constantly requires a high level of attention to ensure that the data is consistent, accurate, and reliable. By continually validating the data, we can identify any type of issues that affect the data collection routine, adjust maintain system performance, and thus ensure high data quality.

3.2.1 Automated flagging with range and gradient checks

Automatized data plausibility checks of raw observations have been accomplished in quasi real-time. Although data-driven modelling holds great promise to improve the data quality in the future, initial trials required supervised data to yield satisfactory results (Russo et al., 2019; Disch et al., in prep.; Disch and Blumensaat, 2019). Presently, two plausibility check routines, namely a range and a gradient check are executed on a regular basis (currently every 24 hours) and return flags to the "Datapool". The range check is an effective measure to consider prior knowledge on the geometry of the sewer and the physical measurement principle in quality checking (Bertrand-Krajewski et al., 2008; Clemens et al., 2021). A range check is necessary to ensure that the measured values fall within a valid range (min, max). Values outside of this range may indicate an issue with the measurement or the sewer system itself and are flagged. Gradient checks are useful to detect sudden changes in a time series, which can help to identify events of malfunctioning or abnormal system behaviour (Clemens et al., 2021; Russo et al., 2019). The latter involves looking for abrupt changes in the order of one magnitude from one data point to the next. By detecting these artefacts, it may be possible to identify the beginning of an event, such as a sudden spike or drop in a measurement. However, it is important to validate the results of gradient checks to ensure that the detected changes are meaningful and not just random fluctuations in the data. Despite the fact that many sensors are similar, parameterization of both routine checks is specific for each sensor.

The results are intentionally stored as additional information "flags" (to the raw data). This flagging helps to avoid redundancies, improves reproducibility, and saves computing resources. The data user can retrieve data with or without flags from the integrated SQlite database using one of the provided data-access packages (DAP) provided in package D. DAP's are available for different programming languages, e.g. Julia, Python and Matlab/Octave. The result of the automated flagging is either *True* or *False* for each individual data point. As data is recorded, these results are visualised in an internal maintenance dashboard and trigger maintenance alerts as appropriate. Only data flagged as *True* is shown in the web viewer (C) (see Section 3.4).

3.2.2 Regular data consistency and homogeneity checks

To enhance data quality, we performed regular checks to ensure data consistency and homogeneity. We also identified and rectified any significant errors resulting from device failures, monitoring configuration changes, clogging, cross-section alterations, and other potential factors, thus ensuring unambiguous data.

In addition to regular data consistency and homogeneity checks, advanced data validation methods, such as anomaly detection, have been proposed in literature (Russo et al., 2019, 2021; Clemens et al., 2021). However, these are a highly challenging topic of current research (Deheer, 2022; Disch et al., in prep.; Disch, 2022) and no standard methods are available yet for sewer data. We highlight this as a great opportunity to do further research with this dataset in Section 4.1.

3.3 Rainfall-runoff model

In addition to sensor data, we provide a hydraulic model implemented in EPA-SWMM, which entails information on underlying infrastructure, flow topology, network engineering, operation and functioning during dry and wet weather. It has been adjusted to the monitoring data using optimization and likelihood-based approaches and describes the rainfall-runoff process largely satisfactorily, with a Nash-Sutcliffe Efficiency (NSE) of 0.7 in calibration and a NSE of 0.4 for predictions of the WWTP inflow. Initially, the model was implemented in MikeUrban (DHI, 2015) by a consultancy for the drainage master plan. It was then converted to EPA-SWMM implementation to allow open access. The model only covers the combined sewer system, i.e. it ignores storm sewers and the associated drainage area, which represents about one third of the total drained area. The model consists of 246 sub-catchments that drain into 427 junction nodes connected by 431 links, with seven CSO structures. Hydrological and hydraulic parameters were adjusted after the conversion to EPA-SWMM, while the structure and hydraulic characteristics of the pipe system remained unaltered. Flow balancing has been conducted to validate the model for dry weather conditions. The model accommodates groundwater infiltration, and it incorporates two methods (base-flow infiltration; rain-dependent inflow) to incorporate this aspect into the model. The model was calibrated manually and automatically using simulated annealing based on the NSE coefficient at the entry of the WWTP based on the rainfall period between March and May 2016. Both calibrations obtained NSE values over 0.5 in the calibration period. Wani et al. (2022) performed a spatially differentiated calibration using the Bayesian parameter inference approach and the NSE as the different points as objective functions. They concluded that the calibration of the model using spatially distributed data did not lead to better parameter estimates in Fehraltorf. The SWMM model structure files as well as input files, flow patterns are available in package B. As any other drainage system, the sewer network in Fehraltorf is subject to changes. For instance, with the installation of new flow limiting hardware in 2019-2020, modifications were made to the network that are not yet considered in the currently provided model structure. Further information on the rainfall runoff model, as well as on the accompanying data can be found in the SI. For example, we identified small discrepancies in elevation between the manholes of the SWMM, the provided digital elevation model and our own reference measurement with differential GPS (SI Section 8).

3.4 Accessing and exploring the monitoring data

To enable open access to data, we have adopted the FAIR (Findable, Accessible, Interoperable, and Reusable) principles (Wilkinson et al., 2016). To make the data findable, we ensure that our data is described and labelled using appropriate keywords, standardized formats, and persistent identifiers (see Section above). In this way, researchers and users can easily find and access the data they need. To make them accessible, we make our data available through ERICopen (Eawag Open Research Data Institutional Repository) (see Section 6). We also provide documentation on how to access and use the data. To make the data interoperable, we structure our data using open, standardized formats that can be easily integrated into existing workflows and systems (SQLite, csv, ascii). We also provide meta-data on how the data was collected, processed, and analysed to facilitate reproducibility and reuse in table "*source_meta_data*" (SI Section 5). To make the data reusable, i.e. to ensure that data can be used for multiple purposes beyond the original research project, we provide the data under an open license that permits non-commercial reuse and redistribution of the data with attribution (Section 6).

Unfortunately, the ERICopen implementation provides access to the data, but yet only very limited exploration capabilities. Therefore, similar as in previous work (Špačková et al., 2021), we provide a webapp[7] as pre-viewer to the data, which has been implemented in R-Shiny and is an efficient way to explore and filter the data, e.g. by signal type, source or location (Figure 6).

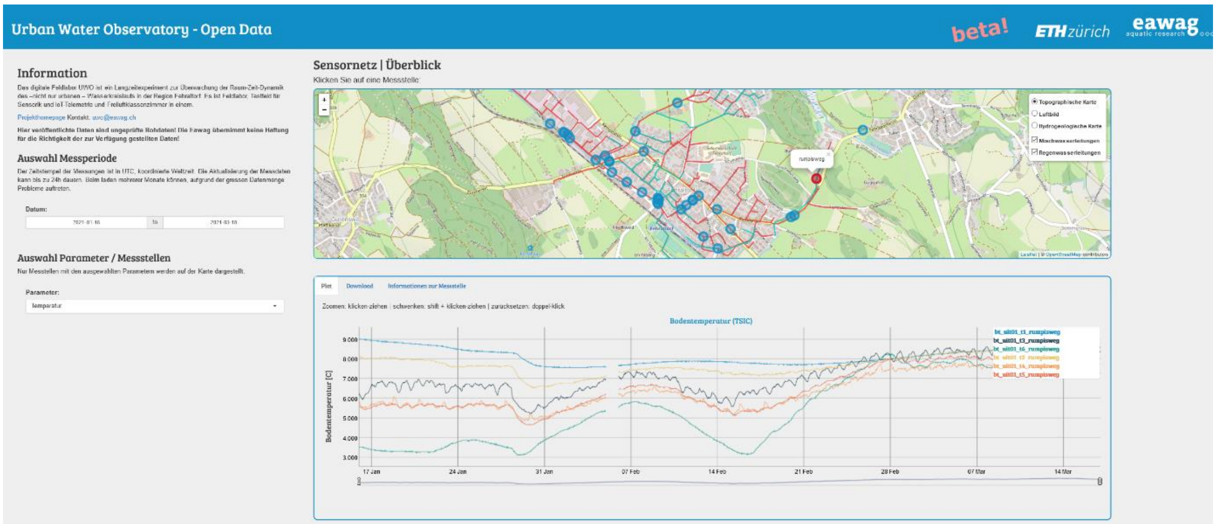

Figure 6: Online pre-viewer to the UWO Opendata set, which includes information on the location of the data source, as well as time series and meta-data on the characteristics of the sensor and the monitoring site. Web access: https://uwo-opendata.eawag.ch/

4. Research opportunities

The UWO dataset is valuable for researching urban drainage processes and evaluating process-based and data-driven methods with real-world data. Here, we will briefly highlight five research opportunities using the UWO dataset to: i) develop automated data quality checks, ii) assess spatio-temporal variations in groundwater infiltration, iii) improve event-duration monitoring of combined sewer overflows, iv) investigate sewer heat transfer and v) assess wireless sensor network performance. More details on the individual opportunities are given in the SI Section 10.

[7] https://uwo-opendata.eawag.ch/

4.1 Anomaly detection of sewer monitoring data using semi-automated machine learning approaches

Advancements in sensor technology and data transmission have transformed process monitoring in drainage systems through a wealth of data (Ruggaber et al., 2007; Kerkez et al., 2016). However, the traditional manual data preparation is insufficient for extracting useful information. Automated approaches are needed for real-time sensor data validation, if needed with human intervention to improve data quality. Machine learning, especially unsupervised methods, can enhance real-time data preprocessing and ensure comprehensive data quality assessment. Detecting anomalies in recorded data is crucial, but complex data-driven methods often fail with urban drainage data (Deheer, 2022). In this study, we compared three data validation methods (ARIMA, Autoencoder, One-class SVM) using UWO dataset time series of levels, flow and temperature. We employed filtering, smoothing, and imputation preprocessing steps and generate a reference time series with synthetic errors. We used the popular F1 score to evaluate the performance to correctly detect anomalies (see SI Section 10). Our results suggest that the simultaneous analysis of related signals enables anomaly detection, and more preprocessing with human intervention improves the F1 score (Figure 7).

The F1 scores for monitoring data with synthetic errors during wet weather (Figure 7, right: D_{wet}) are substantially better (ARIMA: 0.71, OCSVM: 0.65, autoencoder: 0.73) than for real measured data (average: 0.43). As expected, preprocessing (denoising, smoothing, imputing) aids anomaly detection and ARIMA fails with incomplete series. We also find that partitioning the data by weather enhances anomaly detection. ARIMA and Autoencoder methods show promise with synthetic data, but their superiority over OCSVM diminishes with real measurement data.

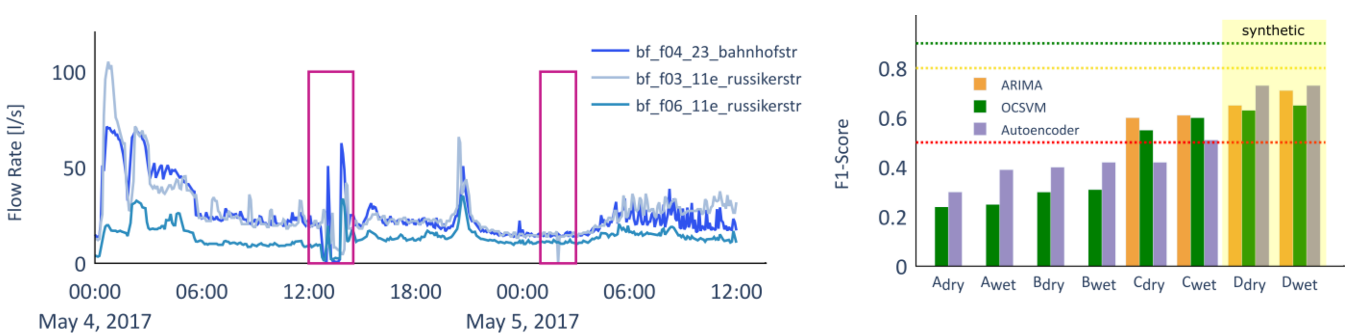

Figure 7, left: Observations with potential anomalies. The highlighted data show the benefit of multiple sensors in detecting anomalies. While the high variability on the left is reflected in all sensors, the one on the right only appear in a single sensor. Right: F1 scores for different methods for pre-processing (A-D). An F1 score of 0.5-0.8 (between the red and yellow dashed lines) is considered medium quality, 0.8-0.9 good and above 0.9 excellent. For real-world data (A-C), the performance increases with increasing levels of pre-processing. For real-world data, ARIMA performs best and the Autoencoder never reaches the performance on synthetic data (D).

4.2 Quantification of groundwater infiltration

Infiltration in urban drainage systems has detrimental effects on wastewater treatment efficiency and increases costs, because it dilutes sewage, reducing biological treatment efficiency, and overloads the drainage system during rain (Staufer et al., 2012). To estimate groundwater infiltration (GWI) rates in the Fehraltorf sewer network, we analyzed long-term flow recordings, focusing on dry weather night-minimum flows and excluding rain-induced infiltration. Using the night-minimum flow, GWI rates were estimated at the catchment outlet and two transfer flows in the Fehraltorf sewer network.

GWI rates ranged from 10 to 15 Ls^{-1}, depending on the season (see SI Section 10). The detailed monitoring data revealed spatial variations in GWI with changing seasons. For example, in April 2018, a high groundwater table affected 256 out of 459 manhole inverts, while in October 2018, only 100 manholes were impacted (Figure 8). Future work can incorporate the spatially differentiated GWI rates into the hydraulic sewer network model to improve the predictive capabilities.

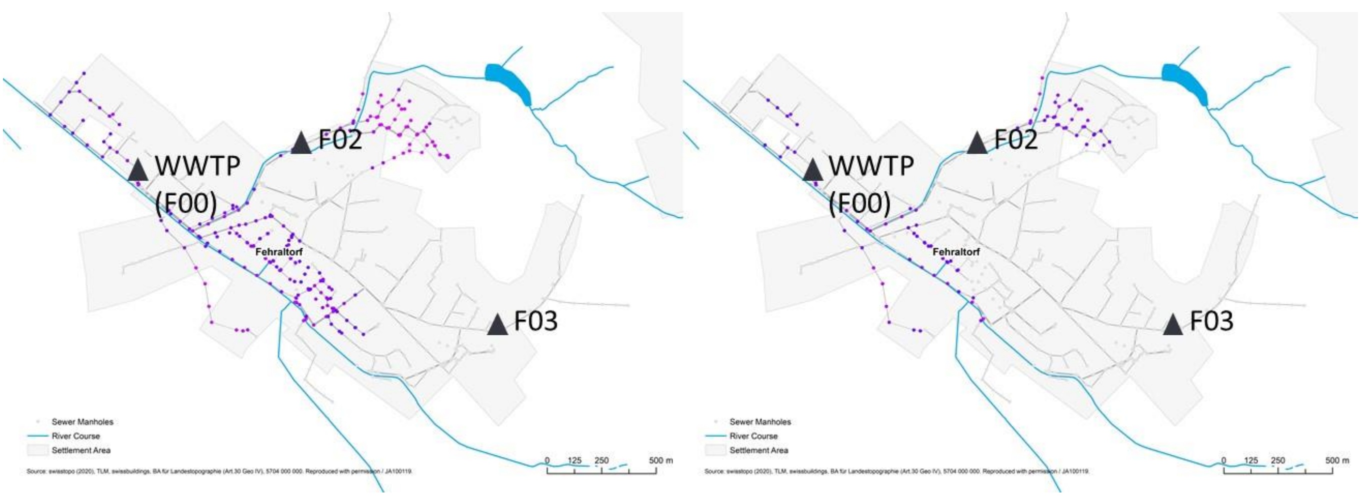

Figure 8 left: 256 sewer manholes in the Fehraltorf network are affected by groundwater in April 2018. The darker the colour the more are manholes submerged in GW. Right: 100 sewer manholes in the Fehraltorf network are affected by groundwater in October 2018. The darker the colour the more are manholes submerged in GW.

4.3 The value of redundant sensors in event-duration monitoring

Assessing CSO activity through tank level monitoring is crucial for quantifying pollution and optimizing sewer networks. To date, more and more countries implement data-based compliance assessment of CSOs and make CSO spill data, e.g. from event duration monitoring, available to the public (Rieckermann et al., 2021; EC, 2022). However, ensuring data quality is a challenge and research explores various monitoring techniques to make data-based compliance assessment more reliable.

In the UWO, we equipped some CSO tanks with multiple ultrasonic and capacitive sensors to independently monitor overflow duration to investigate how redundant signals would reduce uncertainty of CSO event-duration monitoring (SI Section 10).

The results shown in Figure 9 (right) demonstrate that comparing the capacitive sensor signal with the level signal greatly improves data confidence and allows for post-calibration. With only the tank level sensor, incorrect level sensor processing severely underestimated CSO activity and resulted in 50 % less cumulative overflow duration in a period of 1,077 days.

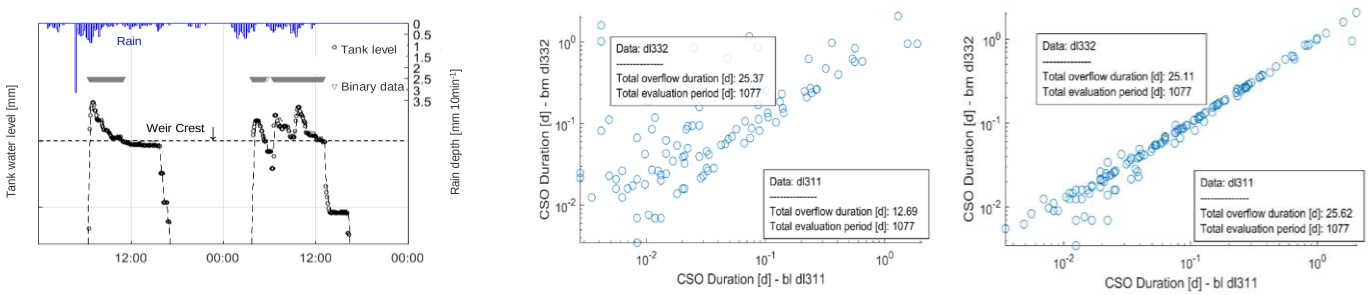

Figure 9, left: Continuous tank water level (dots) and binary information (triangles), derived from the capacitive sensor signal, reflecting the overflow activity for a period of two days for which two independent overflow events where recorded. Monitoring frequency are five minutes, for rainfall it is one minute. Middle and right: event-specific overflow durations derived from one capacitive sensor (bm_dl332_rub_morg) and one ultrasonic level sensor (bl_dl311_rubmorg_inflow). Middle: level data have been used with original (erroneous) information on sensor settings (distance sensor head – tank invert). Right: information on sensor offset settings have been revised.

4.4. Assessing latent heat transfer in sewers – detecting condensation

Accurate predictions of sewer heat transfer processes are important for in-sewer processes (Huisman, 2001), and heat recovery (Figueroa et al., 2021; Abdel-Aal et al., 2019; Hadengue et al., 2021). Latent heat transfer in sewer systems has been often disregarded by urban drainage modellers (Elías-Maxil et al., 2017), although there is no quantitative evidence that latent heat transfer is not important. Using a subset of the provided temperature time series, we investigated the difference between headspace and bulk liquid temperatures to identify conditions for A) condensation and B) evaporation (SI of Figueroa et al., (2021)). We analyse the provided temperature data in three locations dl933, dl935 and dl931 (Figure 10). We find that condensation takes place in April when the typical temperature difference between the sewer headspace and the bulk liquid temperature is -2 K. In contrast, with warmer ambient air and headspace temperatures, evaporation occurs. Maximum differences can amount to 5 K, at location dl931. Based on these results, Figueroa et al. (2021) conclude that latent heat transfer should not be neglected, especially in areas with high relative velocity and lower bulk liquid depth in the sewers, i.e. in steep catchments and peripheral regions. Even in scenarios with high relative humidity values, latent heat processes play a crucial role and should be considered. This makes the provided temperature data an ideal source to further developing heat exchange models for sewer networks.

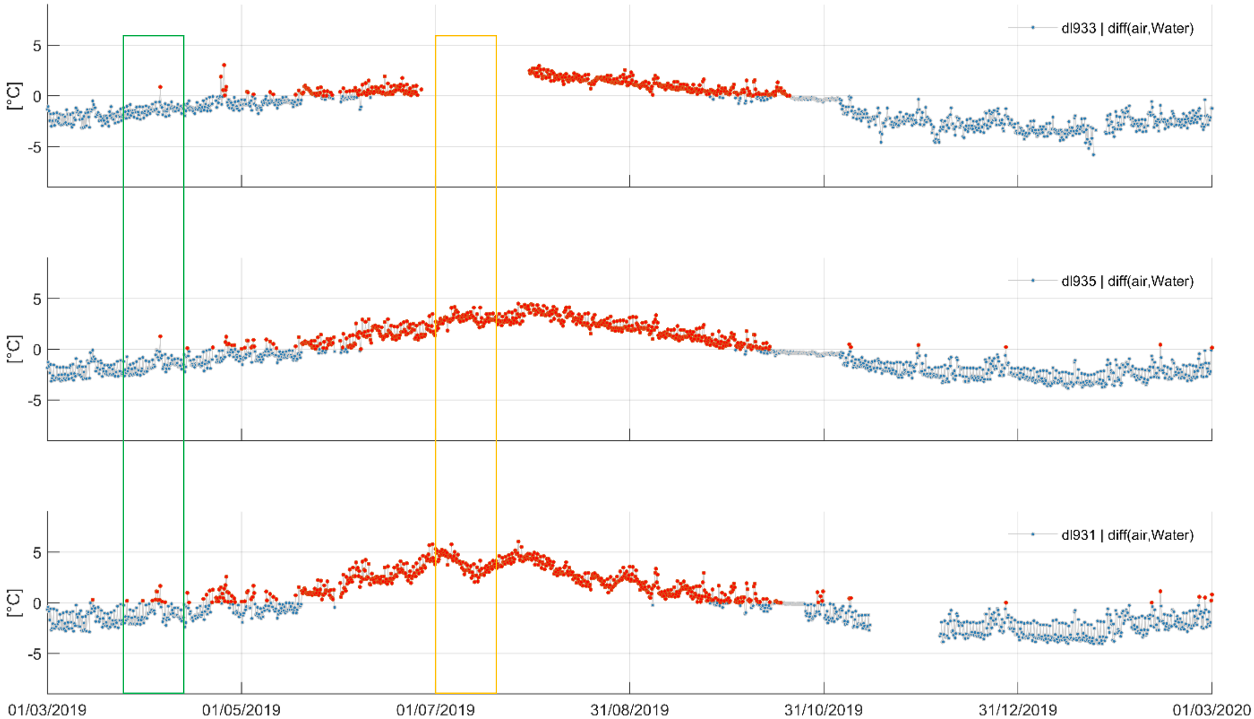

Figure 10: The temperature difference between the sewer headspace and the bulk liquid observed at three specific locations in the main collector. Red dots indicate periods of evaporation (higher temperature in the headspace compared to the bulk liquid) and blue colours indicate periods of condensation (inverse temperatures) (from the Supporting Information of Figueroa et al. (2022)).

4.5 The performance of a LoRaWAN network for underground applications

Sewer systems lack proper monitoring due to limited low-power wireless data transmission technology. LoRaWAN shows promise for underground monitoring but its performance in harsh conditions and metal-covered manholes is uncertain (Ebi et al., 2019). We evaluated the quality of LoRaWAN network service by comparing packet error rates (PER) of underground and above-ground sewer nodes. PER represents the percentage of data packets that fail to reach their destination due to transmission errors Table 2. Our results show a low average PER of about 5% and a median of 3% across practically all nodes. Interestingly, 1-minute nodes perform slightly better, likely due to radio transmission from aboveground locations (SI Section 10).

Future research can analyse the IoT radio network to explore LoRaWAN networks' potential for underground monitoring, advancing the maintenance of infrastructures such as heating, water, and electricity networks. Investigating environmental factors' impact, such as heavy rainfall or extreme temperatures, on key radio performance indicators could provide further insights into LoRaWAN networks' suitability for underground monitoring.

Table 2: Summary statistics of the Quality of Service of the LoRaWAN wireless network. The mean of sensor median packet error rates (PER) was computed from weekly values for two groups of gateways (1min, 5min). While the global average of data packet losses is very low, i.e. approximately 5 %, median values indicate an even lower packet loss, i.e. 3 %. Also, the 1-minute nodes perform slightly better, most likely since a fair number of these nodes do not transmit from underground locations.

Median PER [-]	# of packets per week	2017 (# Sensors)	2018*	2019	2020	2021	2017 - 2021
1-min nodes	10,080	0.026 (2)	0.020 (13)	0.058 (34)	0.048 (36)	0.037 (31)	0.050 (39)
5-min nodes	2,016	0.056 (34)	0.043 (46)	0.055 (58)	0.061 (58)	0.032 (47)	0.056 (68)

6 Data availability

Data from the Urban Water Observatory are available at the Eawag Research Data Institutional Repository (ERIC/open)[8]. The dataset is available for reuse under a specifically designed data use agreement, which was created with the municipality of Fehraltorf and permits non-commercial reuse for scientific discovery. License terms apply. The geodata by swisstopo is supplied with conditions of use, which comply with the legal basis. The conditions of use enable free use for all purposes and oblige the user to indicate the source as “Source: Federal Office of Topography swisstopo” or “© swisstopo”.

7 Conclusions and Outlook

Monitoring sewer systems and making the data publicly accessible will be of paramount importance in the future, as sewer systems are under-monitored in relation to their substantial monetary value and service. Therefore, we provide this open dataset of urban hydrological data, which not only provides a detailed description of the rainfall runoff process, but also includes information on sewer temperatures and the functioning of our LoRaWAN wireless network, which will be important to expand the application of sewer monitoring data in solving current and future problems. Based on the results and experience in the collection and curation of the UWO Dataset, we draw the following conclusions:

- IoT wireless sensor technologies and low-cost sensors present an opportunity to revolutionize sewer monitoring by providing real-time data on key system parameters., but they do not make traditional monitoring techniques obsolete. We have learned that it pays to establish a monitoring backbone consisting of a few full-featured but (often) maintenance-intensive sensors, such as rainfall and pipe flows. Due to their high measurement accuracy, their data can be used as reference observations to establish flow balances. Flow sensors are a crucial component of any sewer monitoring system, allowing operators to detect issues such as blockages or leaks better than level sensors. Rainfall sensors are equally important to correctly interpret the hydraulic monitoring data, providing insights into the impact of weather on the sewer system and helping operators anticipate issues such as overflows or flooding. The monitoring and the use of wastewater thermal energy, e.g. for heat recovery, is still in its infancy, although it is comparably simple and can help authorities optimize the operation of the entire wastewater system.
- To fully benefit from monitoring data, it is crucial to ensure that streaming sensor data is sufficiently reliable. We found that automated state-of-the-art quality checks, such as range and gradient checks, can help to identify and correct any errors or anomalies in the data. Nevertheless, regular manual data consistency checks, e.g. with simple physical models as Manning-Strickler, and homogeneity checks are also critical to ensure the accuracy and reliability of sensor data.

[8] https://opendata.eawag.ch/

- Automated data validation seems crucial for handling a multitude of sensor signals, such as those from over 30 or 40 devices. While it aids in minimizing the workload associated with sensor upkeep, based on our experience, it is not an all-encompassing solution. First, sewer flows and qualities are highly variabile and seemingly stochastic, even in dry weather. Second, it is difficult to ensure reliable rainfall, flow and level monitoring data with a high accuracy, because access to the underground system is laborious and dangerous and maintaining sensors in the hazardous environment is challenging. This is even more true for utilities, where the value of monitoring data is often not recognized. To ensure data quality, more research is needed, possibly using more advanced methods and analyses. In our experience, using long time series of data and processing data from nearby sensors was especially promising. To have generally applicable methods, much more openly available, annotated monitoring data would be needed, probably at a scale comparable to the large image and text databases which have been at the heart of the recent successes in image segmentation and large language modelling. Nevertheless, the available data and metadata of the UWO data can be a role model to test modern data-driven approaches, such as GANs, or LSTM models.
- For sewer processes, such as infiltration or combined sewer overflow modelling, the data provide a very detailed picture of the functioning of a sewer system. In addition, it could be useful to detect causes of bias between the model and environmental factors, such as weather or temperature, the built environment, e.g. land use, or sensor failures. They lend themselves to test hybrid models or data assimilation approaches.
- For the LoRaWAN research opportunity, we find that data packets can generally be transmitted from nodes located in sewers if the nominal distance between node and gateway is less than 500 meters. Open topics would be the performance during wet weather or how the underground location affects PER rates, e.g. by transmission through metal manhole covers.
- Meta-data are essential to correctly interpret sensor signals. A formalised description of meta-data will help to standardise sensor signal interpretation. More coordinated efforts are needed to introduce open data and open science concepts into the urban drainage community. Among other things, this requires a more standardised description of exchange formats for monitoring data, in a similar fashion as OGC-standards, WaterML and InfraML, and a standardized description of meta-data to enable machine-to-machine communication. Ultimately, to effectively manage and analyse monitoring data from wastewater systems, it would probably be important to augment existing ontologies, such as the Smart Cities[9], that can be used for semantic annotation. These ontologies would provide a standardized framework for defining and describing the meaning of terms and concepts used in the monitoring data, making it clear what type of information is being provided.

[9] https://github.com/Azure/opendigitaltwins-smartcities/

8 Author contributions

MM conceived the original idea of making water infrastructure “transparent”, through advanced monitoring. FB conceptualised the idea, designed the data collection campaign, identified the study area, initiated and maintained the cooperation with the municipality/communal utility, and continuously coordinated field work and research studies. Since 2016, all authors contributed to adapting the concept and design of the study, discussing the methods, and research opportunities and to the writing or revising the manuscript. Specifically, SB and CE developed, customised, tested and prepared monitoring and data communication hardware for the field. SB and CE implemented and maintained devices in the field, with support from AD and FB. SB, FB, CE, CF and AD collected and curated the observation data.

Andreas Scheidegger (Eawag), Uwe Schmitt (SIS) and FB conceptualized the data pipeline for data collection, data quality control and data storagel. Uwe Schmitt, CF, AD, SB, CE and FB implemented the data pipeline in software. CF improved the preliminary version of the webapp to view the data in RShiny. CF, with the support of AD maintained the webserver and continuously ensured the interoperability of all data pipeline components . FB, MBR and JR prepared the SWMM model, with support from Joshi Prabhat and Claudia Keller. SB, FB and AD prepared the Geodatabase and accompanying information, such as metadata on sensor functioning and maintenance. JR conceptualized the manuscript, with the help of FB, SB and AD and prepared the submitted paper, which was approved by all authors. FB, MM and partly JR supervised the project.

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