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D2.2: Performance and return on investment of urban water systems

Benefits obtained through the deployment of digital solutions

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Abstract	The present report summarizes the benefits of the eleven digital solutions demonstrated within DWC-WP2 in the form of fact sheets. The document aims to help cities and water utilities in finding appropriate solutions for their operational, environmental or public health deficits. The report is the final version which was submitted in Nov. 2022 after incorporating the recommendations and amendments by the EC.

Dissemination level of the document

X	PU	Public
	PP	Restricted to other programme participants

	RE	Restricted to a group specified by the consortium
	CO	Confidential, only for members of the consortium

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R5	2022-11-20	David Steffelbauer	Updated Version of the report
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* The version convention of the deliverables is described in the Project Management Handbook (D7.1). *D* for draft, *R* for draft following internal review, *S* for submitted to the EC and *V* for approved by the EC.

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Executive summary

This report contains the demonstration outcomes of 11 digital solutions under WP2. For each solution, it describes the demonstration site and challenges, the achievements in terms of performance and return on investment and the approach to assess and quantify the benefits via solution-specific key performance indicators (KPIs). **Section 1** introduces the solutions and their targeted impacts. The following **section 2 to 12** document the demonstration of the digital solutions (DSs). For each DS, the solution itself and demonstration are outlined, KPI definition is documented and return on experience is assessed. At this stage, all DS are finalised, the KPI are defined, and fully assessed. This deliverable is further part of the full "environment" of WP2 deliverables. The baseline for implementing and demonstrating the DS is detailed in D2.1 Implementation plan (M12), and technical specifications and expected benefits and recommendations for replication are given in D2.4 Technology report.

Key elements on performance of each solution as well as key learnings per solution are the following:

<table>
<tr><td>Mobile application for data collection of drinking water wells</td><td>DS7.1</td></tr>
<tr><td colspan="2">Performance improvements

The baseline scenario is that field workers document observations onsite with paper forms that are later copied into a database. The mobile app "DW well diary" provides a streamlined, more efficient flow of information. Performance improvements are:
40 % reduction of time needed to document field work at drinking water wells, resulting in cost savings of more than 13 k€ per year.
2.8 % reduction of errors compared to manually entered data, leading to additional cost savings of around 12k€ per year.</td></tr>
<tr><td colspan="2">Key learnings

The DW well diary enables central storage of data that have not been stored before at BWB. The user-centric development resulted in the high acceptance of the potential end-users and made it possible that new features could be prioritized according to end-users needs. Standardization is a prerequisite for digitalization, and the lack of it is a barrier to implementation. An additional effort was needed for the internal standardizing of procedures and the extension of the internal database.</td></tr>
<tr><td>Forecasting tool for strategic planning and maintenance of drinking water wells</td><td>DS7.2</td></tr>
<tr><td colspan="2">Performance improvements

The baseline scenario is the internal tool that BWB is currently using to assess its strategic planning and maintenance need. The developed machine-learning approaches to identify well ageing and decreasing well capacity in routine operation to prioritize maintenance or reconstruction needs in DS7.2 lead to higher forecast and prediction accuracies, such as:</td></tr>
</table>

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• An increase in the coefficient of determination (r^2) from 0.38 to 0.78. • A reduction in root mean square error (RMSE) of 18.2 %.	
Key learnings Within the project, the applicability of machine learning to support well managers was successfully demonstrated. However, further research is needed to fully implement the solution in the business processes of water utilities. Nevertheless, the project results and the data show foundations for building well management tools.	
Sensor and smart analytics for tracking illicit sewer connection hotspots	DS9
Performance improvements The baseline scenario is the current practice of finding illicit connections with CCTV inspections. The hotspot screening with smart sensors and data analytics shows the following performance increase: • The hotspot screening efficiency increased tenfold, as the search area can be reduced to ≈10 % of the network with the proposed methods. • The overall OPEX reduction is around 32 % compared to commonly used techniques.	
Key learnings The smart sensors are easy to handle and install. However, some weak points in the sensors (e.g., electrical cables) need to be more robust for permanent use inside sewer systems. Furthermore, several network connection and data transmission problems were leading to data loss. This has to be improved as well for a permanent installation.	
DTS sensor for tracking illicit sewer connections	DS8
Performance improvements The baseline scenario is the current practice of finding illicit connections with CCTV inspections. The hotspot pinpointing with distributed temperature sensing (DTS) shows the following improvements compared to the baseline scenario: • Detection of additional illicit connections is around 0.67 per km • This comes at an increase in OPEX of a factor of 3.5	
Key learnings Typically, access to the sewer system is realized via a sewer manhole that allows easy and safe access, e.g., via a fenced-off manhole at a parking lot or another location with no or only little traffic. In the Berlin Fennsee area, however, no such manhole was available as all storm sewer manholes were located in the middle of streets, making installing the devices more complicated.	
Low-cost temperature sensor for real-time combined sewer overflow and flood monitoring	DS14

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Performance improvements	
Performance improvements The baseline scenario is either no monitoring of combined sewer overflows (CSOs) as in Sofia or the detection with commonly used measurement devices (i.e., water level sensors) as in Berlin. The novel low-cost sensors showed the following performance compared to the baseline: • The low-cost sensor can detect the same number of CSO events as conventionally used sensors, hence, enabling the detection where such sensors are not available • The detection accuracy is the same as for water level sensors • The accuracy of detecting the duration of CSO events is slightly over-estimated (around 7 %) • The CAPEX of the low-cost sensors is significantly lower than conventionally used sensors. Offline devices lead to a 77-92% reduction in costs per unit, and online sensors to a 46-78% reduction, respectively.	
Key learnings The sensors are surprisingly easy to install, both for the online and offline versions, even for inexperienced operational teams, and sensor maintenance tasks such as replacing batteries and cleaning are also easy. However, the hydrodynamics of the offline sensors could be improved to avoid the loss-malfunctioning of those sensors due to shear and strain produced by wastewater. Also, the battery life of the sensors could be increased to reduce the frequency of manhole maintenance activity for operators. A possible application barrier of the smart sensors might be the higher OPEX costs due to the higher maintenance effort of the in-situ sensors.	
Smart sewer cleaning system with HD camera and wireless communication	DS15
Performance improvements The baseline scenario for cleaning consist of standard cleaning of sewer pipes plus an additional inspection process with CCTV inspections or an electronic mirror. The smart device that combines sewer cleaning and inspections in one process resulted in the following performance: • The cleaning effort increases by a factor of 2.3 • However, the inspection efficiency of the new device is ten times higher compared to standard cleaning and two times higher when compared to an electronic mirror • The gained financial value for cleaning, quality control, and condition assessment reduces the CAPEX by 200k€ (no additional inspection truck needed) and halves the OPEX (no additional inspection team is required).	
Key learnings DS15 has proven to be a perfect additional tool for the cleaning team, used for several use cases, where the CCTV was not applicable (e.g., useful for egg-shaped profiles and pipes with small diameters). Although the usage of DS15 results in additional time and effort for	

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the operational team, the video quality is excellent and gives good information about the pipe's structural and operational condition.	
Sewer flow forecast toolbox	DS11
Performance improvements The baseline scenario for the comparisons is that the current forecasting system is calculated regarding inflow measurements at the WWTP and the existing inflow forecast "STAR". The improved machine learning (ML) sewer inflow forecast toolbox increased the forecasting performance in the following way: • Accuracy of short-term forecasts (three hours) increased by around 30% (measured w.r.t. RMSE) • Dry weather flow forecasts for more extended time horizons (12-36 hours) had an accuracy score of around 75-80% • With the new method, wrong WWTP operations could be reduced by 90%.	
Key learnings The ML tool shows more flexibility and a higher degree of automation in the model building than the currently used model. Additionally, the ML model, once it is trained, is way faster, allowing forecasts in the order of seconds. Furthermore, model training with the ML tool is easier, and longer forecasting horizons could be used if desired.	
Interoperable decision support system and real-time control algorithms for stormwater management	DS12
Performance improvements The two baseline scenarios are (1) an integrated control strategy currently used by BIOFOS and (2) an alternative control strategy using a HIFI model. Results for the developed digital solution have shown that: • a by-pass volume reduction of 820.000 m^3 or equal to a 25% savings can be achieved with the new strategy • nitrogen can be reduced in a range of 7 % to 19 % depending on the baseline control strategy • a CAPEX reduction of 75 Mio € can be theoretically achieved with the novel control algorithms.	
Key learnings Some improvements are still needed to use the HIFI models as a decision support tool. The performance quality of the forecast models had to be assessed and ensured at multiple stages, i.e. before and after operationalization. Moreover, the evaluation of the operational system forecasts depends on the occurrence of wet-weather events over which they could be performed. Regarding the development and implementation of control scenarios,	

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BIOFOS needed to consider the technical viability of options (i.e., in the model setup) and practical considerations, such as if these control options could be implemented in real life.	
Web platform for integrated sewer and wastewater treatment plant control	DS13
Performance improvements The web platform lets shareholders download data and integrate them into their control strategies. Improvements assessed within workshops and through co-creation with different utilities were: • An increased usage of the digital solution utility buy-in with 80 % participation • That the dashboards are used by the top management	
Key learnings As data is communicated via different sources and protocols, the plan was to utilize communication standards to minimize development overhead. However, being flexible in handling data was determined to be a better approach, as no such standard exists. The FCF platform has a convincing modern, intuitive visualization interface and is a substantial improvement to the SAMDUS platform. The performance/ speed to display data in FCF has been tested and evaluated multiple times and has surpassed BIOFOS expectations.	
Active Unmanned Aerial Vehicle for the analysis of irrigation efficiency	DS5.1
Performance improvements A new method for the remote detection of water stress with an active Unmanned Aerial Vehicle (UAV) and multi-spectral imagery has been developed. The solution's performance is compared with two baseline scenarios: (1) visual inspections only and (2) with visual inspections plus ground sensors. The inspection performance in terms of the spatial, temporal coverage of a field to water- and nutrient stress, overall costs, and data quality doubled compared to baseline scenario 1 and still increased by a factor of 1.4 compared to baseline scenario 2.	
Key learnings The practical application of UAVs, satellites and ground sensors highlighted opportunities. The digital solution enables the mapping of stress conditions, a spatially distributed phenomenon. The end-user could adapt the irrigation and check the effect by evaluating the KPI over a given temporal range (not necessarily the overall season).	
Match-making tool between water demand for irrigation and safe water availability	DS5.2
Performance improvements The digital solution supports the redesign of irrigation schemes by considering the potential of water reuse and establishing a new communication channel to connect the water provider and the end-user (farmers) through a user-friendly web app/webpage. Compared	

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to boarder irrigation, 68% of water, 48% of fertilizers, and 6802kg of CO_2 emissions can be saved annually. In comparison to drip irrigation, the savings are 29% of water, 100% of fertilizers, and 6911 kg of CO_2 per year.
Key learnings The design and development of the MMT highlighted opportunities and issues. The impacts can be minimal in case of less sensitive growing stages, low-stress meteorological conditions and short interruptions. At the same time, they can be tragic in case of crucial growing stages, high-stress meteorological conditions and prolonged disruption. The impacts can be minimal in case of less sensitive growing stages, low-stress meteorological conditions and short interruptions, while they can be tragic in case of crucial growing stages, high-stress meteorological conditions and lengthy interruptions. A possible limitation of the solution is related to the availability and quality of water from the WWTP. A relevant lesson learned is the necessity to define a common way to exchange data efficiently and safely.

This document is an update of the last performance report delivered in M42. Updates include: An overview table in the executive summary highlighting the key elements on performance and learnings from the experience for each digital solution, as well as some minor correction of typos and symbols as suggested by the reviewers.

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1. Preface

European cities face different challenges to achieve sustainable management of urban water systems, e.g. the over-exploitation of surface waters and the effects of climate change competing with a growing demand for liveable and resilient cities. Mobile devices, real-time sensors, machine learning, artificial intelligence, cloud solutions, and other exponential technologies can significantly improve the management of water infrastructures. They can boost the quality of services provided to citizens and foster collaboration between utilities, authorities and citizens. Further, they can improve operational efficiency, workforce utilization, reduce environmental impacts, ensure compliance, and facilitate achievement of sustainability goals and resiliency commitments.

In work package 2 of the digital-water.city project (DWC), eleven digital solutions[1] have been tested and assessed regarding their potential to improve the performance and return on investment of water infrastructures, the latter mainly related to cost savings in the short and long-term, e.g. via predictive maintenance and strategic planning tools. Figure 1 shows the eleven solutions and their addressed domain in the water cycle.

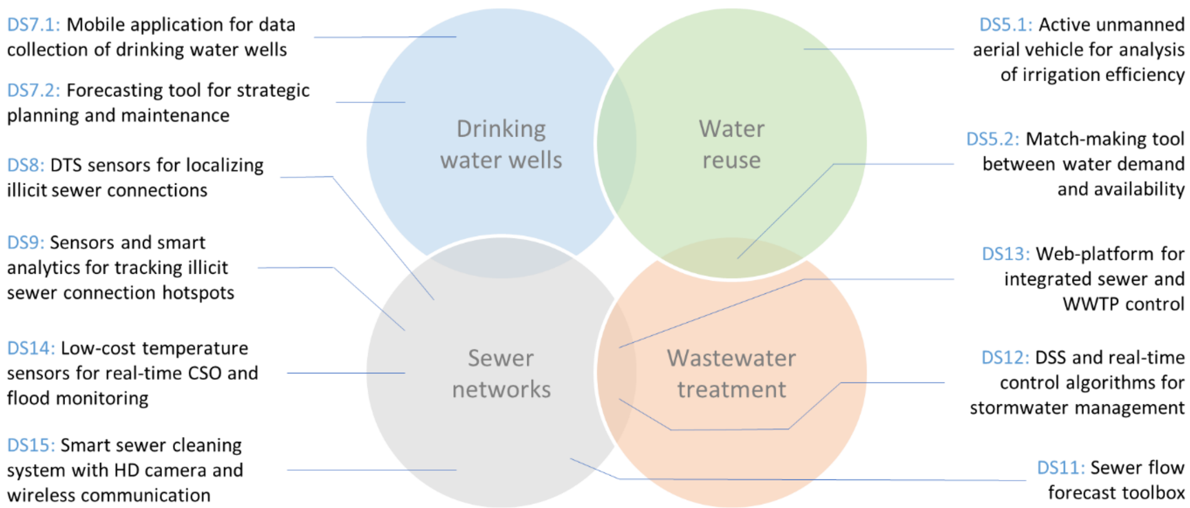

Figure 1: The digital solutions of DWC-WP2 and their addressed domain in the water cycle.

The present report describes the main benefits of the digital solutions – quantified through large-scale demonstration projects via defined performance indicators – in the form of fact sheets. Each chapter refers to one digital solution and was written by the representatives of the respective solution (technology provider, utility or research partner). The solutions are presented along the water cycle starting with the drinking water domain (DS7.1 and DS7.2), continuing with sewer networks (DS9, DS8, DS14 and DS15), closely linked with wastewater

[1] The full list of digital solutions can be consulted at https://www.digital-water.city/digital-solutions

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treatment (DS11, DS12 and DS13), and finishing with water reuse (DS5.1 and DS5.2). The main added values and benefits of the solutions are summarised in Table 1.

Table 1: Main added values of the eleven digital solutions of DWC-WP2, grouped to i) reduction of environmental impacts, ii) operational improvements, iii) cost savings and iv) improved collaboration between stakeholders.

Digital Solution	Reduction of environmental impacts	Operational improvements	Cost savings	Improved collaboration
DS7.1: Mobile application for data collection of drinking water wells		✓	✓	✓
DS7.2: Forecasting tool for strategic planning and maintenance of drinking water wells		✓	✓	
DS9: Sensors and smart analytics for tracking illicit sewer connection hotspots	✓		✓	
DS8: DTS sensor for tracking illicit sewer connections	✓		✓	
DS14: Low-cost temperature sensors for real-time combined sewer overflow monitoring	✓		✓	
DS15: Smart sewer cleaning system with HD camera and wireless communication (DS15)		✓	✓	
DS11: Sewer flow forecast tool box	✓	✓		✓
DS12: Interoperable DSS and real-time control algorithms for stormwater management	✓		✓	✓
DS13: Web-platform for integrated sewer and wastewater treatment plant control				✓
DS5.1: Active Unmanned Aerial Vehicle for the analysis of irrigation efficiency	✓	✓		
DS5.2: Match-making tool between water demand for irrigation & safe water availability	✓	✓		✓

All of the digital solutions have multiple positive effects, as outlined in detail in the following chapters. In the domain of drinking water wells, main benefits of the demonstrated solutions (DS7.1 and DS7.2) are operational improvements and cost savings. In the domain of sewer networks, the solutions (DS9, DS8, DS14 and DS15) mainly contribute to a reduction of environmental impacts and cost savings. Solutions that address both the sewer network and the wastewater treatment plant (DS11, DS12 and DS13) also improve the collaboration between stakeholders, besides operational, environmental and economic benefits. The solutions related to water reuse (DS5.1 and DS5.2) have environmental and operational benefits and also facilitate collaboration between stakeholders.

The document aims to help cities and water utilities in finding effective solutions for their operational, environmental or public health challenges. The document also targets the industry and private sectors by summarising the practical experiences obtained in the

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demonstration projects. The report is a draft version and will be updated and published as a final version in November 2022. A technical description of each digital solution can be found in D2.4 (technology report).

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2. DS7.1: Mobile application for data collection of drinking water wells

2.1. Digital solution

Drinking water wells are the main infrastructural assets for utilities to produce drinking water. In order to fight well-ageing and maintain the well's groundwater production capacity, iron-ochre formations need to be periodically removed in the process of well regeneration. In addition, periodic maintenance of submersible pumps and frequency converters is necessary to ensure a reliable drinking water production.

Well data consisting of static information such as design and construction as well as operational data such as current discharge rates, water levels, previous maintenance, and water quality data are typically stored in well management database(s). However, in the field, paper format is still widely used to record monitoring and maintenance data and these work reports are later on transferred manually to the database(s). Further, technical specifications of the well or previously recorded information on well maintenance or are not fully accessible while being on the field. The developed digital solution "DW Well Diary" (DS7.1) consists of (i) a user-friendly web application (frontend) accessible from mobile devices (see Figure 2) and (ii) a backend solution that facilitates the exchange of data between the well database and the mobile application. The solution aims at making well data easily available to staff in the field and facilitate online-documentation of maintenance actions. It will be fully integrated with the existing operation and maintenance work processes. The provision of digital well information and work reports on site by a mobile device application will improve guidance and on-demand information for field workers and facilitate interactive flow of information enhancing performance and resource efficiency in monitoring and maintenance.

2.2. Demo description

Berliner Wasserbetriebe (BWB) is operating approximately 650 groundwater abstraction wells and some thousand observation wells. Together with another hundreds of observation wells owned by Berlin's water authority they form the subsurface assets for drinking water production in Berlin.

In nine water works, BWB is producing up to 1 Mio. cubic meters of drinking water per day. Well operation is automated and controlled from the water works. In order to secure a reliable water supply 24 hours a day, the wells are regularly inspected and maintained. This includes laboratory analysis of well water quality, pumping tests to test well capacity, CCTV inspection for visual diagnosis, mechanical cleaning as well as chemical regeneration procedures to remove for example iron ochre deposits. More and more, wells are equipped with a set of sensors to monitor flow, water level and heads. Sensor equipment varies depending on site and age of the well installation. The three largest of BWB's nine waterworks control operation of the six smaller waterworks and form internal teams, which are responsible for operation and maintenance of wells and infrastructure in the three main waterwork-groups.

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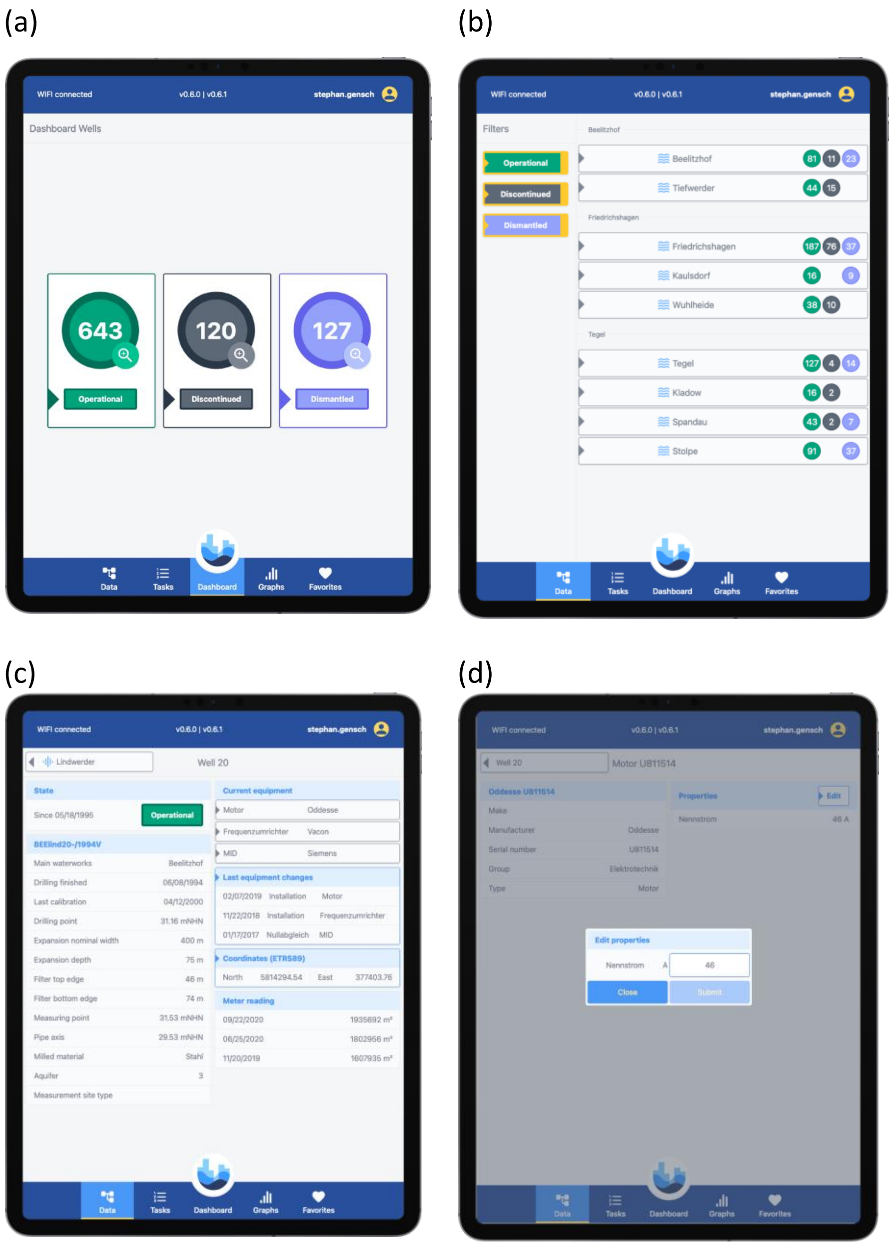

Figure 2: The "DW Well Diary" dashboard as part of the progressive web app (a) with Waterworks hierarchical view with filter options (b), Well detail view (c) and Change of property for well equipment and well parameters (d).

The development of the digital solution DS 7.1 "DW Well diary" followed the principles of agile software development, meaning that the features of the DS were incrementally developed and tested in prototypes with a team of end-users, selected from operating staff of the three main waterwork-groups. Based on the prior developed concept of the Well Diary and a first

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definition of business processes and data to be included in the Well Diary, a first prototype was developed, visualizing concept and basic functions. In January and May 2021, two workshops were held with the end users where the features of the prototypes were discussed in detail and compared to user expectation and needs. User requirements were adapted and additional features identified. Also, these workshops revealed differences in internal business processes, such as exact work-flows and naming conventions between the test users from the three main waterwork-groups. This shows that standardization of business processes is often a prerequisite for digitalization.

The following table shows an overview of data which can be assessed using the Well Diary:

- technical specifications of the well: date of borehole drilling, borehole diameter, depth of the well screen, material of the well screen, aquifer used, variable frequency drive type;
- technical specification of well equipment (variable frequency drive, MID, filter;
- maintenance actions: date of equipment change, date of MID calibration;
- operational data: water production at the time of the last well capacity test;
- coordinates of the well, link to GIS.

2.3. Assessment of the digital solution

Within the DWC project, a working prototype of the "DW Well Diary" has been developed. It is currently running in a test environment within BWB's IT infrastructure. At the premises of BWB, there are two environments for integration testing and productive operation, namely stage and prod. On stage, all final integration testing has been done on current data of the Db2 database within all working parameters of the infrastructure and environment. A working prototype of the "DW Well Diary" has been deployed on stages 1 and 2 of the Vragments dedicated DWC system and also on stage 1 of the BWB environment. Transfer to productive operation is planned after integrating the mobile app into the existing LDAP user authentication and after adding of additional features which were defined during user workshops in DWC but could not be finished within the project. Also, software maintenance needs to be provided and contracted for the prod environment. As full-scale roll-out of the developed digital solution is therefore planned, the assessment of the "DW Well Diary" assumes implementation in the prod environment and two key performance indicators (KPI) were defined as summarised in Table 2.

Table 2: Overview table of KPI assessment

KPI	Short description	Quantification
Reduction of time needed to document field work at drinking water wells	Any maintenance of drinking water wells includes documentation in a central well database. The "DW Well Diary" allows direct input into the well database and eliminates the need for paper documentation and later transfer to the database.	$1-\frac{time_{Docu,DW\ Well\ Diary}}{time_{Docu,current}}$ = 40 %

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KPI	Short description	Quantification
Reduction of errors of manually entered data in the database	The error-prone manual transfer of data to from paper to a database is replaced by direct data entry in the field. Based on the estimated number of data entries per year and an average error rate during manual data transfer, the number of data errors prevented by implementation of the DS is calculated.	$\mathrm{ER} \times n_{entries} = 2.8\% \times 8190 \approx 229$

2.3.1. KPI 1: Reduction of time to document field work at drinking water wells

In order to estimate the time saved during documentation of drinking water wells, the number of maintenance documentation processes was estimated:

- Change/maintenance of submersible pump: 1x /5 years,
- Maintenance of frequency converter unit: 2x / 5 years,
- Well regeneration: 1x / 5 years,
- Flow meter maintenance: 1x / year,
- General maintenance, function test, inventory: 1x / year.

Thus, for each drinking water well, a total of approximately 2.8 maintenance processes per year were estimated, which require documentation. For the time needed to document maintenance actions, 0.3 hrs per process were estimated for documentation in the field and 0.2 hrs per process to later transfer these data into the database (including plausibility check).

Table 3: Time needed for documentation of maintenance processes in hours per process for the ***paper-based*** *documentation and subsequent transfer to the digital database (current practice) and the* ***electronic*** *documentation directly in the field (DS7.1).*

Process	Paper-based	Electronic
Documentation in the field	0.3	0.3
Plausibility check and transfer into database	0.2	None
Total time	0.5	0.3

Electronic documentation using the “DW well diary” eliminates the need for data transfer and allows for implementation of automatic plausibility checks during data entry. Accordingly, approximately 40% of the time needed for documentation can be saved by implementing the “DW well diary”. This number is in line with research comparing paper-based and electronic data collection processes in clinical trials which report 49% to 62% of savings that the electronic process brings[2].

[2] Pavlović, Ivan; Kern, Tomaz; Miklavcic, Damijan (2009): Comparison of paper-based and electronic data collection process in clinical trials. Costs simulation study. In: Contemporary clinical trials 30 (4), S. 300–316. DOI: 10.1016/j.cct.2009.03.008.

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Considering the total number of 650 drinking water wells currently operated in Berlin, the total reduction of time needed for maintenance documentation can be estimated to be approximately 364 hours/year, corresponding to personnel costs of approximately 13.000 €. An additional, not quantified benefit of the “DW well diary” is the immediate availability of data in the database, as data do not need to be transferred manually, which currently takes between several days and a few weeks.

2.3.2. KPI 2: Reduction of errors of manually entered data in the database

Data errors are frequently found in electronic data repositories in general but also in the internal well database to which the “DW well diary” is linked. Although such data errors are discovered from time to time, the data quality of the internal well database is generally good and could not be checked in detail during the project. It is assumed that data errors mainly happen during manual transfer of data from paper to the electronic database. Following Hong[3] who investigated error rates in a clinical data repository, the error rate during manual data transfer into the database is assumed to be 2.8 %. Based on the number of data entries per work process, the total number of work processes per year (see 2.3.1) and the total number of wells (650), the total numbers of data entries per year is estimated to be 8.190. Implementing the “DW well diary” will thus potentially prevent approximately 230 false data entries into the database. Assuming an additional effort to 1.5 hrs of work to find, correct and double-check any false data entry, this corresponds to approximately 344 hrs/year, corresponding to personnel costs of approximately 12.000 Euro.

Beyond these KPIs, the introduction of the “DW well diary” additionally enables a central storage of data which currently have not been stored in electronic form or decentralized. During the development process, a number of work processes was identified which were not yet digitized, but relied on pen-and-paper-processes. Some of these processes were standardized and additional data structures needed to be added to the internal database. This is necessary to efficiently control technical processes and guarantee safe drinking water production as shrinking production reserves are less able to compensate for downtimes. The “DW well diary” will therefore contribute to making Berlin’s water production more resilient.

2.4. Return on experience

The realized incremental development including early prototyping and continuous delivery enabled the user-centric development of the “DW Well Diary”. Valuable user feedback was collected in digital workshops and enables further development of the prototype. Users’ needs and perspectives were assessed and fed back into product development. The benefits were a high acceptance of the potential end-users as well as high expectations of the end-users regarding features provided to help them in their daily work. Additional features were identified showing the potential of the digital solutions but unfortunately exceeding the

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[3] Hong, Matthew K. H.; Yao, Henry H. I.; Pedersen, John S.; Peters, Justin S.; Costello, Anthony J.; Murphy, Declan G. et al. (2013): Error rates in a clinical data repository. Lessons from the transition to electronic data transfer--a descriptive study. In: BMJ open 3 (5). DOI: 10.1136/bmjopen-2012-002406.

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available capacity of the project. This process also made it possible that the features could be prioritized according to end-users needs.

During the prototype workshops, the team of end-users was asked about their expectations on the Well Diary to assess the potential benefits of the solution. A total of five staff members was questioned and the results show that expectations are generally high.

Figure 3 shows the results of collected user feedback on the benefits of the digital solution. While the users agreed that the final product "Well Diary" generally saves time (Figure 3a), the estimated share of work where the "Well Diary" could be used in the future is expected to be in the range between 10 % to > 40 % of the working hrs. at drinking water wells (Figure 3b).

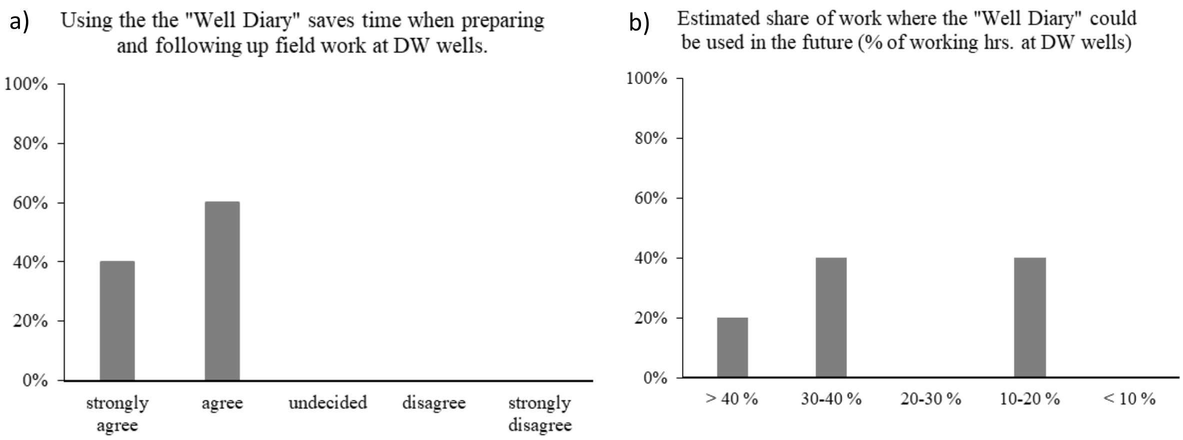

Figure 3: Feedback from prototype workshop participants (n=5) on expected benefits of the Well Diary.

Employee satisfaction was also assessed using data from test user questionnaires (Figure 5). The "Well Diary" is expected to increase the job appeal as well as positively influence the profession (Figure 5 a and b). Average feedback was 4.4, corresponding to an estimated positive to very positive change in job appeal.

(a) (b)

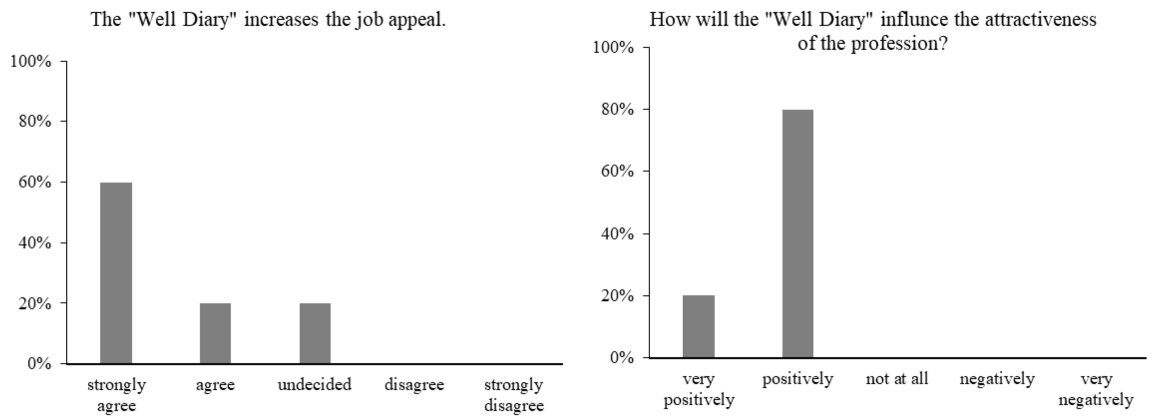

Figure 4: Feedback from prototype workshop participants (n=5) on expected benefits of the Well Diary.

During the development of the "DW Well Diary" it was also found that standardization is a prerequisite for digitalization and lack of it is a barrier to implementation. Additional, unplanned effort was needed for internal standardizing of procedures and the extension of the internal database.

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3. DS7.2: Forecasting tool for strategic planning and maintenance of drinking water wells

3.1. Digital solution

The main reason for inefficient well performance is commonly referred to as well ageing. Deposit formation due to multiply correlated biological, chemical and/ or physical clogging processes in and around the well (Figure 5) cause a decrease in the specific capacity of a well, which is the yield for a given drawdown. This results in higher energy demand for lifting the water and thus in higher costs of abstraction. Regular or on-demand monitoring provides information on the performance and condition of wells and aquifers, and delivers data for advanced statistical analyses to enhance understanding of the processes and provide diagnosis and early-warning to schedule well maintenance in a more proactive manner. DWC therefore aimed at applying machine learning to a set of selected well data in order to better understand the key parameters for well ageing and to project the loss of well capacity for a given time ahead.

Figure 5: left: clogged well, ochre deposits inside the screen; right: clogged pump, ochre deposits at the pump intake, both ©BWB

DS7.2 combines automated data processing of routine monitoring data with machine-learning (ML) approaches to identify well ageing and decreasing well capacity in routine operation and prioritize maintenance or reconstruction needs. The solution has been developed in the statistical programming language R and consists of the core algorithms to (i) pre-process a given set of well data turning them into a data structure providing the explanatory variables to the ML model, (ii) feature selection and assessment of the importance of the selected variables, and (iii) model training and prediction of future loss of well capacity based on selected well characteristics. With this approach, DS7.2 moves from time-based to condition-based maintenance, which makes maintenance more efficient, reduces energy consumption for pumping and avoids downtime of wells.

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3.2. Demo description

The Berliner Wasserbetriebe (BWB) are operating more than 650 vertical filter wells supplying the drinking water for the city's nearly 3.7 Mio. inhabitants from groundwater resources within the city limits. In order to keep performance and water quality as high as possible, these wells require regular monitoring, maintenance and well management.

DS7.2 was developed and demonstrated based on csv-files exported from a db2-database, in the following referred to as "well database". This "well database" consists of a set of tables describing geological conditions, constructive features of the wells, past maintenance events and geochemical analyses of water and ochre samples from the wells. The data set used for DWC contained 6.308 data points of 994 wells and covered a period from the 1950s to 2021, randomly separated into training and test data (80% / 20%).

Current prognosis of well ageing focuses on evaluating the demand for reconstruction of wells and is done by the controlling department of BWB applying an excel-based tool (developed in-house). With this approach, the specific capacity of a well, is projected based on the average development over the lifetime of a well. In parallel, the technical division and the well managers in the waterworks evaluate capacity development, constructive condition, operational boundaries and other factors to assess the maintenance demand of the wells. On average, pumping tests are conducted every two years and maintenance is done every five years. These pumping tests in combination with the well specifics described above provide the data to train the ML model of DS7.2 and to assess its performance.

The development and demonstration of DS7.2 included data pre-processing and statistical analysis to reveal the relevant predictor variables for well ageing and remove strong interdependencies in model input. Correlated numeric variables were identified using the Spearman correlation[4] and categorical variables using the Chi-Square and Cramér's V method[5,6]. For the core ML model, recursive feature elimination (RFE) and Random forest were applied with the full set of input variables to identify a set of 25 relevant variables. The top four predictor variables were (i) well age, (ii) time since last rehabilitation, (iii) number of previous well rehabilitation events and (iv) coefficient of variance in daily abstraction volume.

Further, five statistical and ML-based methods have been tested and compared regarding their capability to predict the specific capacity of a well (i) multivariate linear regression, (ii) logistic regression, (iii) decision tree, (iv) random forest and (v) gradient boosting. The gradient boosting model performed best, with 94% of all data points with a remaining specific capacity

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[4] Daniel, Wayne W. (1990): Spearman rank correlation coefficient. Applied Nonparametric Statistics (2nd ed.). Boston: PWS-Kent. pp. 358–365. ISBN 978-0-534-91976-4.

[5] Pearson, K. (1900): On the criterion that a given system of derivations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science 50(5), 157–175.

[6] Cramér, H. (1946): Mathematical Methods of Statistics. Princeton: Princeton University Press, page 282 (Chapter 21. The two-dimensional case). ISBN 0-691-08004-6

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of below 80% predicted correctly and only 12% false warnings (Figure 6). The root mean square error (RMSE) for the prediction of the exact value for specific capacity (0 to 100%) is 14.8%. The model will now be discussed with the well managers and staff of the technical and controlling division of BWB and tested against currently used tools. Refinement will include the discussion of improvement of data input and results visualization and connection to the BWB-IT and well database systems.

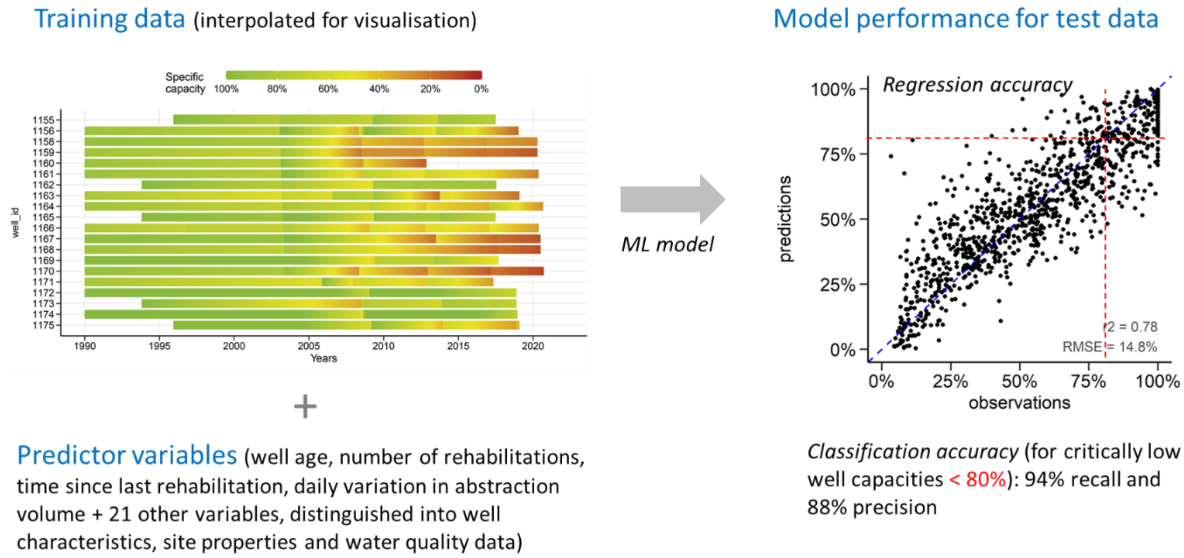

Figure 6: Input data and ML model performance for the prediction of well capacity

3.3. Assessment of the digital solution

The benefits of the solution were assessed via the comparison of the accuracy of prognosis of DS7.2 against the excel tool currently used by BWB (CO-tool). The coefficient of determination (r^2) and RMSE were calculated, of which the first describes to which percentage the variance in the observations can be explained by the model, and the second describes the standard deviation of the prediction error, i.e., the difference between observed and predicted data. The results are summarised in Table 4. Details on considered input data as well as calculations are given below.

Table 4: Overview table of KPI assessment

KPI	Short description	Quantification
Increase in coefficient of determination (r^2)	$r^2 = \Sigma(\beta_i \cdot r_i)$ β_i – standardized regression coefficient for i variables r_i – correlation coefficient for i variables	$r^2_{\text{current practice}}$: 0.38 $r^2_{\text{DS7.2}}$: 0.78 Δr^2: 0.40
Reduction in root mean square error (RMSE) for predicting the specific capacity	$RMSE = \sqrt{((P_i - O_i)^2/n)}$ P – predicted value of the i^{th} observation O – Observed value of the i^{th} observation n – sample size	RMSE $_{\text{current practice}}$: 33.0 % RMSE $_{\text{DS7.2}}$: 14.8% ΔRMSE: -18.2%

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For both tools, predicted numeric values for the specific capacity were plotted against observed values, the linear trendline was added and r^2 and RMSE were determined using the statistical programming language "R" [7].

DS7.2 predicted values are the results of the gradient boosting model for the test data set compared with observations (Figure 6). CO-tool predicted values were taken from a model run of 05th February 2017 for the years 2018-2022 kindly made available by BWB. Observed values were latest pumping test data before rehabilitation events conducted between 31st January 2017 and 31st March 2021 exported from the db2-database. 523 wells contained predicted and observed values. For the assessment of model accuracy of the CO-tool, the prediction for the year nearest to the pumping test date was considered. Data pre-processing was done in Excel.

As Table 4 shows, DS7.2 performed better for both KPIs. 78% of the variance in the observations could be explained and RMSE was at 14.8%, while for the CO-tool, only 38% of the variance was explained and RMSE was more than twice as high. Concerning the set of explanatory variables, DS7.2 uses specific well characteristics identified in correlation plots, while the CO-tool relies on a theoretical well ageing curve, which is however representing the average of all BWB wells with their specific characteristics. From our point of view, a comparison is thus admissible.

3.4. Return on experience

As in previous research on statistical evaluation of well ageing processes, data compilation and remaining data gaps and/or pre-aggregated data are crucial steps and remain as a barrier. Although the data set used to demonstrate DS7.2 was exhaustive, time periods covered by the data were quite different for the single parameters and/or measurement frequencies were too irregular to allow for useful aggregation. For example, operating hours and abstraction volumes between single maintenance events should have been included as key variables, but were not extractable from the given data.

Secondly, so far, no direct connection to the data source was established. Two reasons were identified: (i) data export from inside BWB IT to outside interfaces was assessed to be critical by BWB. In DWC, DS7.1. and DS7.2 were developed independently by two partners Vragments and KWB. Due to this separation, joint "docking" to the data source has been explored only after initial development of both solutions, and (ii) statistical programming language R is widely used at KWB, but not at BWB. Thus, the R code developed provides the core calculations for data processing and ML modelling and includes key tables for indexing and aggregating the input variables, but these need to be provided from the source database and results need to be "handed over" to reporting and visualization tools.

DS7.2 also endeavoured to improve the assessment of the remaining specific capacity by combining measurements of dynamic water level from regular performance monitoring with

[7] R Core Team (2021) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

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continuously measured flow rates and static water level measurements derived from monitoring wells. No correlation could however be established between water level measurements in monitoring wells and abstraction wells allowing for an automated assignment of reference monitoring wells to the abstraction wells under assessment. Linear interpolation was achieved for well data and compared to the monitoring well data. Calculation of remaining specific capacities using static water levels from selected monitoring wells yielded high uncertainties because of impacts from well operation within the galleries and managed aquifer recharge nearby. Training the model with highly uncertain data would potentially decrease overall model performance. Additional static water levels from observation wells were thus not incorporated.

Overall, DS7.2 successfully demonstrates the applicability of data-driven machine learning in order to make optimal use of available well data and support well managers in predicting ageing rates and prioritizing maintenance efforts.

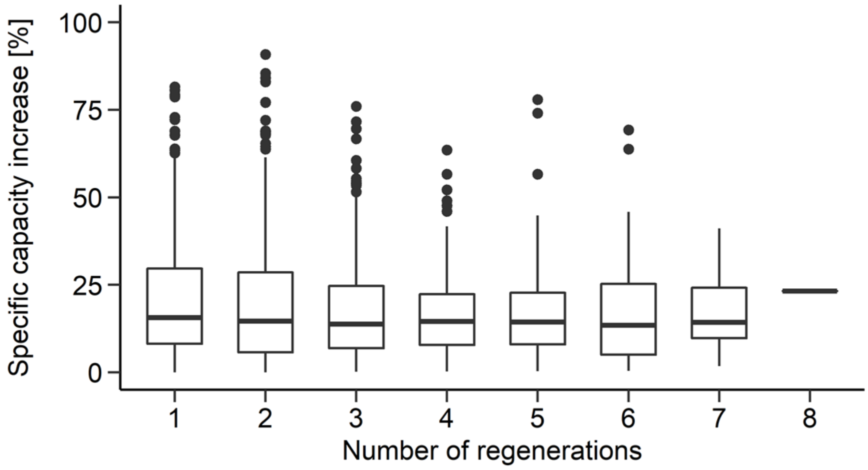

Figure 7: Increase in specific well capacity after regeneration (mean increase after rehabilitation: 16.1 – 18.8 %, independent of number of regenerations)

Due to time constraints, it wasn`t possible to perform the initially planned refinement of the solution within the DWC project, i.e., to also include further analyses such as clustering the ageing curves to narrow down preferred site conditions and factors that accelerate well ageing and transfer of specific capacity prediction into a well condition index. In addition, Qs predictions were only performed for a “do nothing” (i.e., no well renewal / well regeneration) scenario and to be taking “smart” asset management strategies for each well into account, e.g. :

– Should a well be regenerated or build completely new? Depending on the expected Qs increase by well rehabilitation (mean increase after rehabilitation for Berlin: 16.1 – 18.8 %, independent of number of regenerations, see Figure 7) and decrease of well drawdown lowering pumping energy cost.

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- Optimize well rehabilitation schedule (i.e., predict days after which well losses xx % of relative Qs) in order to maintain the raw water production capacity of the Berlin waterworks

Development of such a strategy is required in order to evaluate the potential cost savings by ML-based “smart” asset management and compare it to the EXCEL based investment planning tool for production wells currently used at BWB. Consequently, these topics need to be addressed after the DWC project for making the benefits of using a well specific ML-learning based approach for well asset management more visible and quantifiable for BWB.

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4. DS9: Sensors and smart analytics for tracking illicit sewer connection hotspots

4.1. Digital solution

Illicit connections or sanitary sewage to the storm sewer system, usually due to unintentional errors during sewer construction or rehabilitation, are a significant source of pollution for surface waters and can threaten human health in case of bathing waters. Finding these illicit connections is like looking for a needle in a haystack as illicit connections usually occur at selected points within a large sewer network and usually happen intermittently. The DWC-solution DS9 aims to localize hotspots with a strong indication for illicit connections by combining smart sensors and data analytics. In DWC, these hotspot regions with a sewer length of ~ 1-3 km are then further investigated with DS8 ("DTS sensor for tracking illicit sewer connections") which locates the specific illicit connection based on longitudinal thermal profiles taken at high temporal resolution.

DS9 makes use of two types of sensors, electrical conductivity (EC) sensors and multiparameter (MP) sensors combined with an IoT unit (KANDO's smart unit). The sensors measure the electric conductivity of the flow in the storm sewer network. Based on the continuously measured EC signal and prior knowledge on typical EC values of stormwater (~ 200 µS/cm) and sanitary sewage (> 1000 µS/cm), it is possible to differentiate between both flows and hence identify illicit connections. The sensors are initially installed at the stormwater outlet at the river or lake and then subsequently moved to manholes in upstream sewer sections to systematically narrow down hotspot areas with strong indications for illicit connections.

The EC sensor system consists of an electric conductivity sensor and an offline data logger. The electrical conductivity is recorded every minute. The data is temporarily stored in the data logger and read out in intervals of 2 to 3 weeks via Bluetooth with a laptop. The data sets are saved as CSV files and can be further processed as desired. The batteries have to be changed every two to three weeks.

The MP sensor consists of sensor probes and a data logger with antenna for data transmission via the cellular network. The sensors measure four water quality parameters comprising pH, electrical conductivity (EC), oxidation reduction potential (ORP), and temperature. Data is recorded in the loggers and transmitted to the cloud for storage, analysis and web-based display to users and Kando staff.

In case of the MP sensors, data is acquired every 5 minutes and sent to the cloud three times a day. The batteries have to be changed annually.

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Figure 8: KANDO's smart unit and sensor (left), the EC sensor and logger (right) as well a sensor installed at a sewer manhole (right).

The devices are attached to a string in the manhole. Additionally, a sandbag is installed, which dams up the water and enables the measurement in the water. The installation of both systems can be carried out without going downstairs.

4.2. Demo description

The solution is demonstrated in the catchment of lake Fennsee in the central-western part of Berlin, Germany (see DWC-D2.1), with severe water quality and amenity deficits, suspected to be partly caused by illicit connections. The stormwater catchment has a total area of 220 ha, a sewer length of 39 km, 900 individual pipes, around 800 manholes and approximately 1500 house connections. The settlement structure with 27,000 inhabitants represents a variety in population density and land use. There are three stormwater outlets to the lake and the catchment can basically be divided into three sub-catchments (green, blue and red in Figure 9).

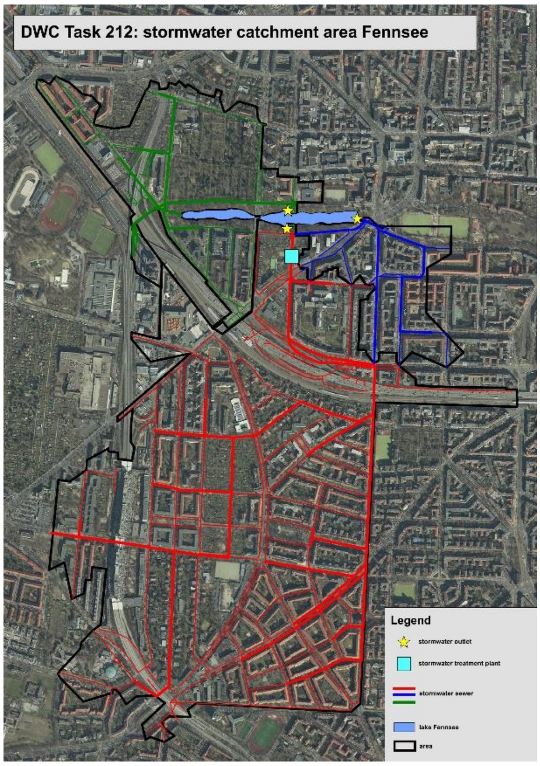

Figure 9: Storm water catchment area of the urban lake Fennsee.

The monitoring campaign started in January 2021. Four MP-sensors and five EC-sensors are used. Starting at the storm water outlets the investigation was carried out backwards through the upstream sewer network at key points in the system. In case of suspicious results, the sensors were iteratively relocated upstream. During two years of investigation, 54 measuring sites have been monitored throughout 20 measuring phases.

For EC-sensor and MP-sensor system two different approaches to evaluate the data have been designed. Regarding the EC values an evaluation scheme to classify the sensor locations according the likelihood of upstream illicit connections has been developed. For each location,

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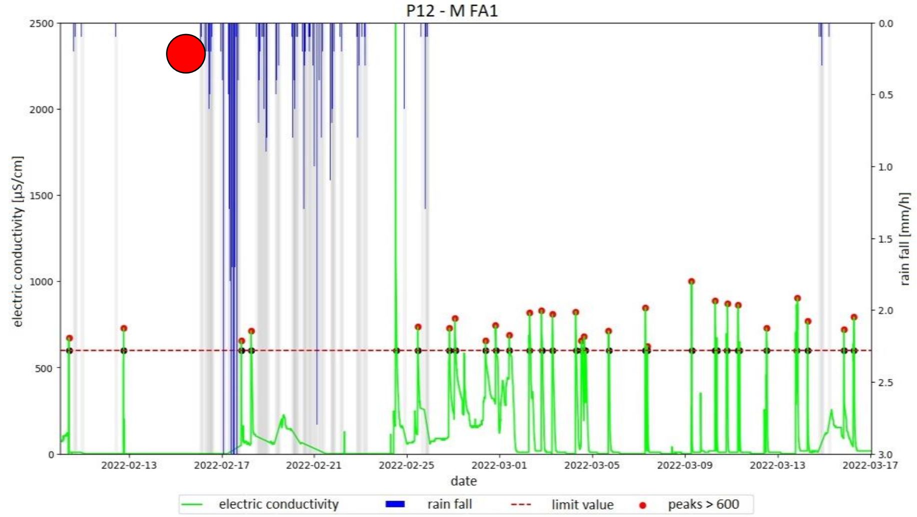
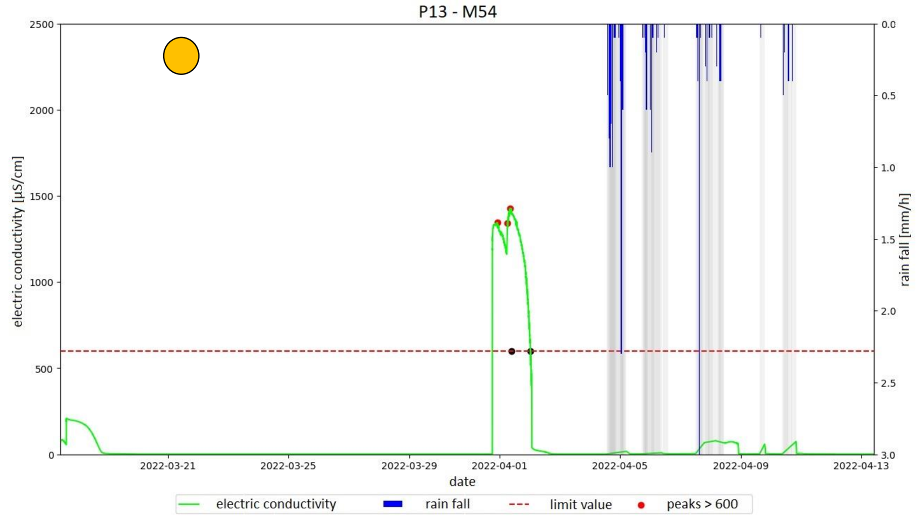
the data of four weeks during dry weather are considered. Wet weather is defined as the time interval from one hour before to three hours after a rain event. Rain events were evaluated from a rain gauge near by the demo area. Exceedances of the limit values 600 µS/cm and 4000 µS/cm are considered and classified into three categories based on a traffic light system, as shown in Table 5. Based on the outlined scheme, a Python script for an automatic evaluation has been developed. Measurement data, which fits with rain events will be eliminated and the script counts the number of relevant peaks above the limit values. Following on this, the program gives an advice of the classification of the measurement site in likely, possible or unlikely.

Table 5: Evaluation scheme

colour	number of peaks > 600 µS/cm / 4 weeks	meaning
	> 4 (or peak > 4000 µS/cm)	Illicit sewer connection is likely
	2 – 4	Illicit sewer connection is possible
	0 – 1	Illicit sewer connection is unlikely





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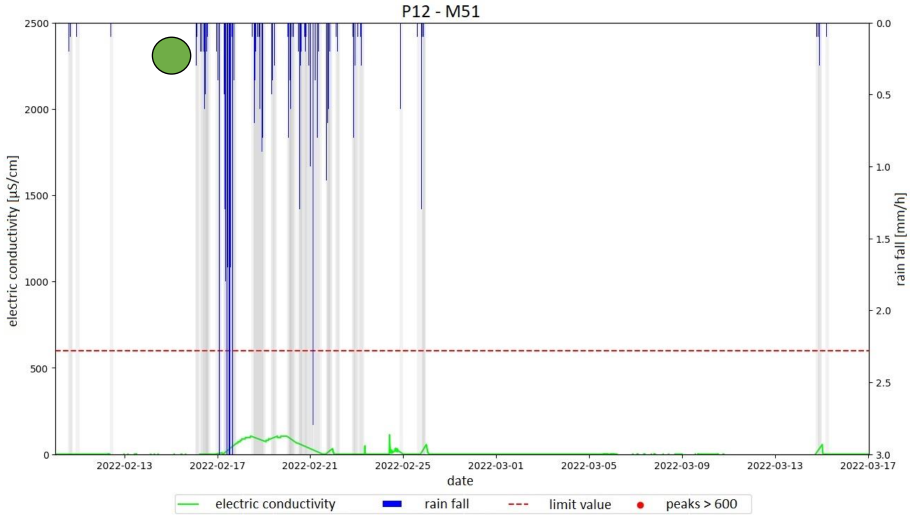

Figure 10: Examples for evaluation: IC likely (top), possible (middle) and unlikely (bottom).

An example for every category is given in Figure 10. The rain events are plotted with blue bars from top. Respectively the excluded rain durations are shown as grey areas. The EC measurement is plotted as a graph over 4 weeks and the critical evaluation value of 600 µS/cm is marked as horizontal red line. All EC peaks above the red line during dry weather periods were counted and the measuring site classified according the traffic light system. To date, the hot-spot analysis is solely based on the results from the EC sensors.

For the MP sensor, data is transformed into actionable insights by Kando's proprietary machine learning algorithms, profiling event characteristics via big data analytics and tracing events back to source. The data-gathering unit is also equipped with a remote sampling unit, real-time quality conditions determines the precise moment when grab samples should be taken in order to generate a representative profile of real-world wastewater contamination, and verify sensor data.

To supplement the analysis performed by BWB team, it is recommended to analyze for diurnal trend and peak hours for the sites defined as having high likelihood of illicit sewer connections in order to better pinpoint the location of the connection. For instance, in site FA1 where Kando sensor was installed during the first quarter of 2022, it can be seen in Figure 11 that by using seasonal decomposition of the data (interval = day) much of the EC fluctuation is explained by seasonality (diurnal changes). The high residual can be explained by an outlier from February 24, which could not be removed since the function requires continuity. This means there's a repeating pattern of EC increase throughout the entire period, and a further analysis can show on which hours this increase takes place.

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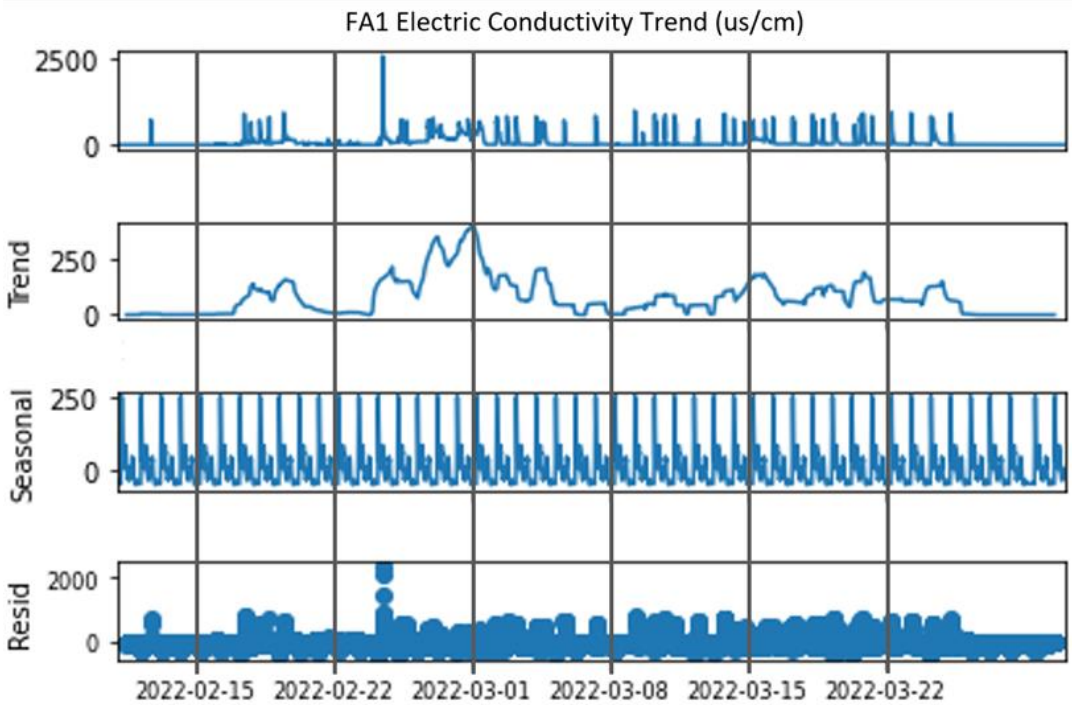

Figure 11: Example for evaluation: Seasonal decomposition of the EC data in site FA1r.

Figure 12 shows a deeper dive into the pattern of discharge. Looking at the diurnal distribution of peak events (where EC> 350 us/cm) it is clear that for site FA1, most events take place during the morning hours, especially during 7 AM (more than 15% of all peak events). This result can either be sourced to an industrial automated process or residential activity. In general, the results of peak events from this site align with other studies and the common knowledge that mornings are the hours of high residential water usage in the morning, followed by a relaxation and an additional evening peak, whereas during the nights there are very few peak events.

This peak events analysis could be performed to distinguish between residential and commercial sources of discharges. Site M25, for instance, displays a different pattern of peak events that could be explained by the fact that this site sits at the heart of a small commercial area which is likely more active throughout the entire day.

(a) (b)

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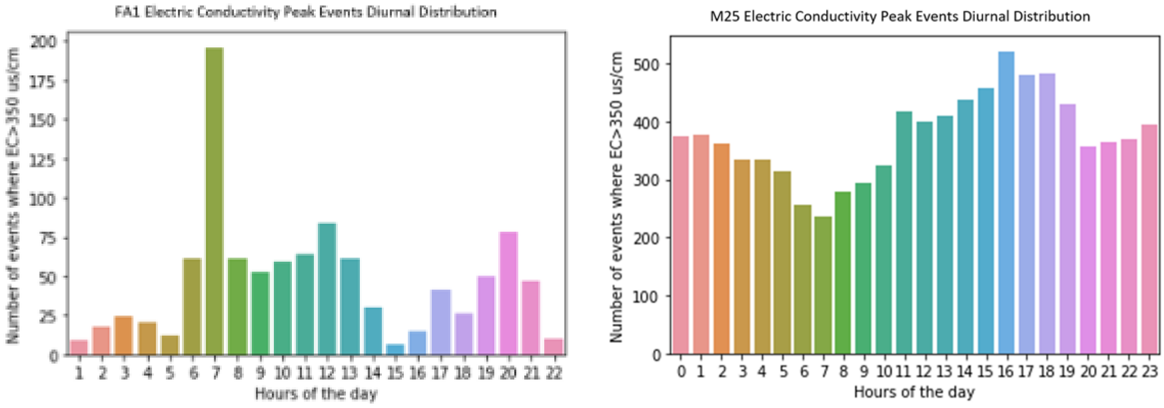

Figure 12: Example for evaluation: diurnal distribution of peak events (EC>350 us/cm) in two sites, FA1 (a) and M25 (b)

In addition to data analysis, the US EPA emphasizes the importance of sampling when performing illicit discharge investigation in order to validate the source of discharges. The EPA recommends on several analytical parameters which can provide better estimation of the source, including Ammonia, Chlorine, Potassium, Phenols, Hardness, etc. Kando's solution enables automatic sampling in case of a jump or trend change in one or all parameters measured (EC, pH, ORP, Temperature). By integrating a sampler to the real time sensors, the investigation can be more accurate and time-saving.

4.3. Assessment of the digital solution

General goal of the DS9 is to narrow down parts of the investigated sewer system with high potential for the presence of illicit connections as hot spots. DS9 will be compared to visual inspections as conventional method in current practice. In the years from 2012 to 2013 more than 1000 visual inspections in nearly 800 sewers have been made in the demonstration area, but no illicit connection could be identified.

The benefits of the solution could be assessed via two defined key performance indicators (KPI) in Table 6. Details on considered input data as well as calculations are given in the subsections below.

Table 6: Overview table of KPI assessment

KPI	Short description	Quantification
Hotspot screening efficiency	Increase of efficiency to narrow down parts of the sewer system with high potential for illicit connections (IC).	$KPI\ 1 = \frac{hotspot\ size_{VI}}{hotspot\ size_{DS}} = 10.5$

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KPI	Short description	Quantification
	Quotient of identified relevant sewers length by conventional visual inspections (VI) and DS 9.	
OPEX ratio for hotspot screening	Costs for hotspot screening by DS9 (personal costs and equipment maintenance costs) compared to conventional visual inspections (VI) within two years of investigation at Fennsee area.	$KPI\ 2 = \frac{personal\ costs_{DS}/2years + equipment\ costs_{DS}}{personal\ costs_{VI}/2years} = 0.68$

4.3.1. KPI 1: hotspot screening efficiency

The evaluation of every measuring site is shown in a geographic context in Figure 13 as colored stars. The color coding is similar to the scheme explained in Table 5. Upstream sewers with potential for illicit connections are narrowed down and marked as red lines similar to the color coding of the traffic light system. Sewers, which are unlikely for illicit connections are marked in green and sewers without detailed information are marked in yellow. Through the investigation with DS 9 twelve hot spots with a strong potential of presence of illicit connections could be identified. In the area of these hot spots, it is possible now to search for illicit connections in detail, either with DS8 ("DTS sensor for tracking illicit sewer connections"), conventional methods (e.g., CCTV inspections) or furthermore with a new deployment of DS9.

All identified hotspots together have a sewer length of 3.7 km. From an original total sewer length of 39 km in the catchment area of Fennsee, DS9 achieved to narrow down the location of interest to an area of 9.5% or by a factor of 0.095. With conventional visual inspections carried out over the last years instead it was not possible to narrow down parts of the sewers system and there are still 39 km of the sewer system left with a possible presence of illicit connections.

The increase of the efficiency to narrow down hotspots is calculated by the quotient of the identified relevant sewer size by conventional visual inspection (VI) and by the digital solution (DS9). DS9 is more effective than conventional visual inspection by factor 10.5.

- Total sewer length: 39 km
- Identified relevant sewer length by VI: 39 km
- Identified relevant sewer length by DS9: 3.7 km

$$KPI\ 1 = \frac{hotspot\ size_{VI}}{hotspot\ size_{DS}} = \frac{IC\ relevant\ sewers\ _{VI}}{IC\ relevant\ sewers\ _{DS}} = \frac{39\ km}{3.7\ km} = 10.5$$

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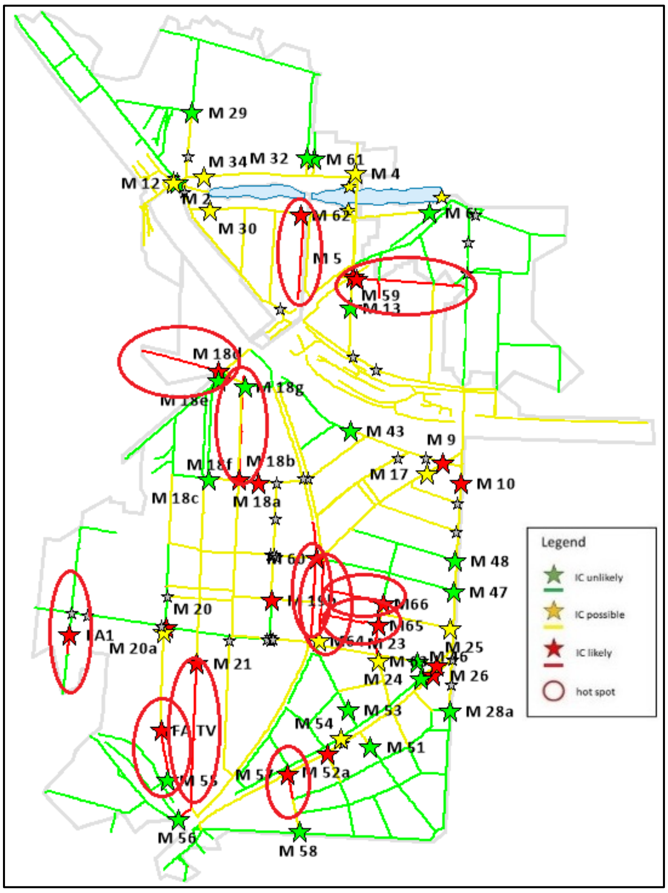

Figure 13: Evaluation of the investigated measuring sites and the interpretation for hot spots.

4.3.2. KPI 2: cost reduction for hotspot screening

A comparison of DS 9 to conventional VI was set up in order to reflect the cost of the digital solution along with the benefits. On a two-year basis of investigation, staff costs as well as the technical costs for the digital solution and conventional visual inspections are compared. For the staff costs, a benchmark system is used, where time needed for the investigation is counted and multiplied with specific personal costs per time.

For the conventional visual inspections, the costs contain basically the time outside in the field to inspect the manholes. In the years 2012 and 2013 the area of the Fennsee was investigated intensively by visual inspections. These costs are calculated for two years of visual inspections by the following values:

- Personal time: [h] 468
- Average specific costs for staff and vehicle: [€/h] 200

For the digital solution, the costs of the measuring systems as well as the staff costs for campaign planning, regular maintenance of the sensors and evaluation of the data must be considered. These costs are calculated by actual project costs for two years of investigation in

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the Fennsee area. The cost for the measurement systems are at 4.760 € for the EC-logger and 1.500 € for KANDOs MP-System. Regarding the workload, three hours for campaign planning and evaluation as well as two hours with two persons for the maintenance in the field are counted for every two weeks.

- Equipment costs for 5 EC-sensor systems: [€] 23800
- Equipment costs for 5 MP-sensor systems: [€] 7500
- Personal time: [h] 364
- Average specific staff costs: [€/h] 90

$$KPI\ 2 = \frac{personal\ costs_{DS}/2years + equipment\ costs_{DS}}{personal\ costs_{VI}/2years} = \frac{\sum\ (personal\ time_{DS} * specific\ staff\ costs) + \sum(equipment\ costs)}{\sum(personal\ time_{VI} * specific\ staff\ costs)} =$$

$$\ldots = \frac{\left(364h * 90\,\frac{€}{h}\right) + (23800€ + 7500€)}{\left(468h * 200\frac{€}{h}\right)} = \frac{64060€}{93600€} = 0.68$$

4.4. Return on experience

Both sensor systems (MP and EC) are easy to handle and install, without going into the manhole. In case of the EC system, it has been shown that the cables aren't robust enough for a permanent use inside the sewer, as five cables got broken within less than one year. Another challenge with the EC system consists in the performance of the logger, which were partly not able to connect to the laptop anymore.

There have been a few starting issues with the network connection and the data transmission of the KANDO smart unit. After solving these problems, the MP sensors and the smart unit worked well. But also, the KANDO sensor system sometimes had software issues which weren't possible to solve in the field.

The KANDO platform gives a comfortable overview of the data, but for including the rain data, the data has to be downloaded and processed further. The KANDO algorithm was developed to detect industrial sewage and should be further adapted for sanitary sewage in stormwater system.

At one measuring site, both the EC and the MP sensor from KANDO have been installed in parallel to compare both sensors. It was noticed that the EC system always measures a minimally higher EC values than the KANDO system. Nonetheless, this offset is not critical as both sensors agree on the observed EC dynamics (e.g., the time of peaks).

It is assumed, that DS9 can be easily transferred to another area or city to investigate illicit connections. The developed measurement and evaluation method were transferred into the daily business of BWB and will be used at other areas soon.

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5. DS8: DTS sensor for tracking illicit sewer connections

5.1. Digital solution

Illicit connections (IC) of sanitary sewage to the storm sewer system, usually due to unintentional errors during sewer construction or rehabilitation, are a significant source of pollution for surface waters and can threaten human health in case of bathing waters. Finding these illicit connections is like looking for a needle in a haystack as illicit connections usually occur at selected points within a large sewer network and usually happen intermittently.

Distributed Temperature Sensing (DTS) is used as the second element in a two-step approach to locate unknown illicit connections in the storm sewer network. While the first step (electrical conductivity and multiparameter sensors, DS9) aims to identify hotspot regions with a high likelihood of illicit connections, DTS is used to pinpoint the exact locations within these hotspot regions.

The DTS solution makes use of fiber-optic cables that are installed over the full length of the considered sewer system and that are connected to a centrally located measuring unit (see Figure 14). Using the principle of laser light reflection (Raman backscattering) the fiber-optic cables can serve as large temperature sensors with a high temporal and spatial resolution (temperature readings typically every 30 seconds and for every 50 cm along the cable).

Using the large dataset of temperature measurements in the storm sewer, illicit connections are identified searching for any type of anomalies in in-sewer temperatures. For instance, a sudden temperature increase at a certain location suggests the inflow of relatively warm (domestic) wastewater at that location. A continuous temperature decrease at a location is often associated with a continuous inflow of, e.g., groundwater or inflowing surface water. The possible source of each inflow can be studied based on its temperature profile (warm/cold, intermittent/continuous, daily/infrequent, etc.). Data evaluation is done by visual inspection of temperature plots as well as by automated algorithms that are trained to scan and identify 'classic' anomalies in the dataset.

Monitoring campaigns generally last a few weeks to include infrequent discharges to the sewer, and to account for holidays (no discharges) and rainy periods (when the inflow of rain disturbs the temperature profile in the sewer and can 'hide' smaller inflows of wastewater

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into the sewer).

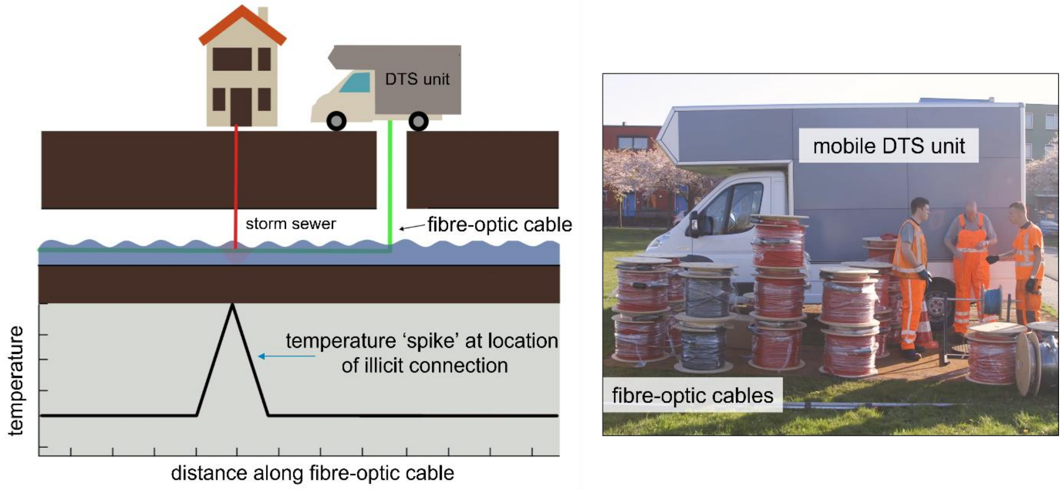

Figure 14: Schematic overview of DTS measurements in a storm sewer (left); example of a mobile DTS unit and several reels with fiber-optic cables prior to installation (right).

5.2. Demo description

The solution is demonstrated in a separate sewer system located in the central-western part of Berlin, Germany. It is the stormwater catchment of the small urban lake Fennsee with major water pollution. There are suspicions that the observed pollution is mainly due to illicit connections, which is the main reason for selecting the site. The entire stormwater catchment has an area of 220 ha, a sewer length of 39 km, around 800 manholes and approximately 1500 house connections. Using EC measurements, about five hotspot areas (with a relatively strong suspicion of illicit connections) have been determined (see DS9).

DTS is applied in a selected hotspot region that comprises approximately 1,500 m of storm sewers around the Wiesbadener Strasse, see Figure 13 (left red circle) and Figure 15 (storm sewers in blue). The DTS unit is set up at the Bezirksamt Charlottenburg at the Sodener Strasse. From there, two fiber-optic cables (cable 1 of 1,500 meter and cable 2 of 1,100 meter, see Figure 15) are used to monitor the full sewer length in the area. Due to dead-end streets and a decentral location of the DTS unit, the required cable length is longer than the observed sewer length.

The monitoring campaign started directly after installation of the cables at September 23rd, 2021 and lasted for five weeks until October 28th, 2021.

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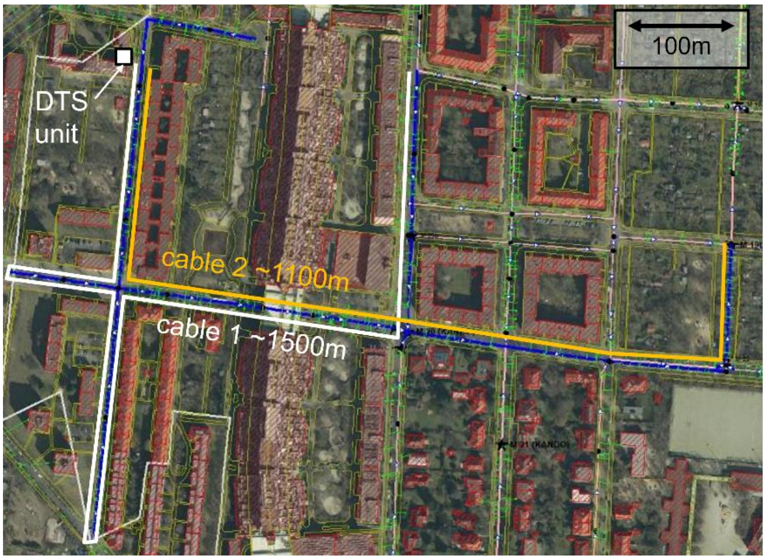

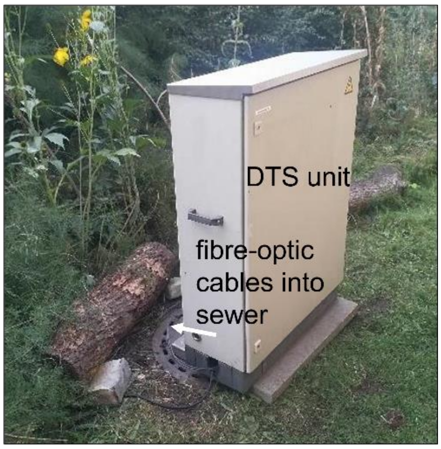

Figure 15: Overview of studied sewer system and fiber-optic cable routes (left); DTS unit installed at Bezirksamt Charlottenburg (right)

5.3. Assessment of the digital solution

The benefits of the solution have been assessed via two key performance indicators (KPI) comparing the application of DTS with that of CCTV inspection. Both of these methods aim at finding the exact locations of illicit connections within a known hotspot area. The results are summarised in Table 7. Details on considered input data as well as calculations are given in the subsections below.

Table 7: Overview table of KPI assessment

KPI	Short description	Quantification
IC detection	(additional) IC detected by DTS compared to CCTV per km sewer investigated	$KPI\ 1 = 0.67\ IC/km$
OPEX ratio	costs of DTS compared to CCTV per km sewer investigated	$KPI\ 2 = 3.55$

5.3.1. KPI 1: IC detection

For this KPI, the number of illicit connections that were found during the DTS monitoring campaign is compared with the results of earlier CCTV inspection in the same area. Using DTS one illicit connections was discovered; with the original CCTV campaign no such connections were found. Over the inspected sewer length of approximately 1.5 km, this yields an additional 0.67 IC per km of sewer length.

$$KPI\ 1 = \ additional\ IC_{DTS} = \frac{IC_{DTS} - \ IC_{CCTV}}{length_{DTS}} = \frac{1-0}{1.5\ km} = 0.67\ IC/km$$

Historical CCTV investigations at the Fennsee serve as a baseline to compare the goals of the digital solution with classical methods. It should be noted that these CCTV inspections were mainly done for detecting structural defects of the pipe, and not specifically for finding illicit connections. In this sense it does not benefit from ‘prior knowledge’, in contrast to the DTS monitoring. In the years from 2010 to 2019 more than 1000 visual inspections (looking into manholes) in nearly 800 sewers have been made, but no illicit connections could be identified this way. Also, in the years 2001 to 2017 roughly 300 sewer sections were inspected using CCTV (inspecting entire sewer sections using a mobile camera). Based on these inspections six sewers with indications for illicit connections have been found. None of these were in the area currently investigated with DTS.

An example of the DTS monitoring results is presented in Figure 16 (left). The horizontal axis gives length along the fibre-optic cable in the sewer, the vertical axis represents time, and the colours correspond to measured temperature values according to the colour bar on the right. In this example we see a sudden temperature increase (from around 20°C to around 35°C) around 09:00 in the morning on September 26th, 2021 at x = 814 m along the fibre-optic cable. This temperature variation is likely due to the inflow of (warm) wastewater from, e.g., a shower or bath. The discharge lasts for a few minutes, after which the in-sewer temperature at x = 814 m slowly decreases to ambient temperatures. The warm water moves downstream while gradually losing its warmth to the surroundings. The location of the observed inflow is indicated in Figure 16 (right).

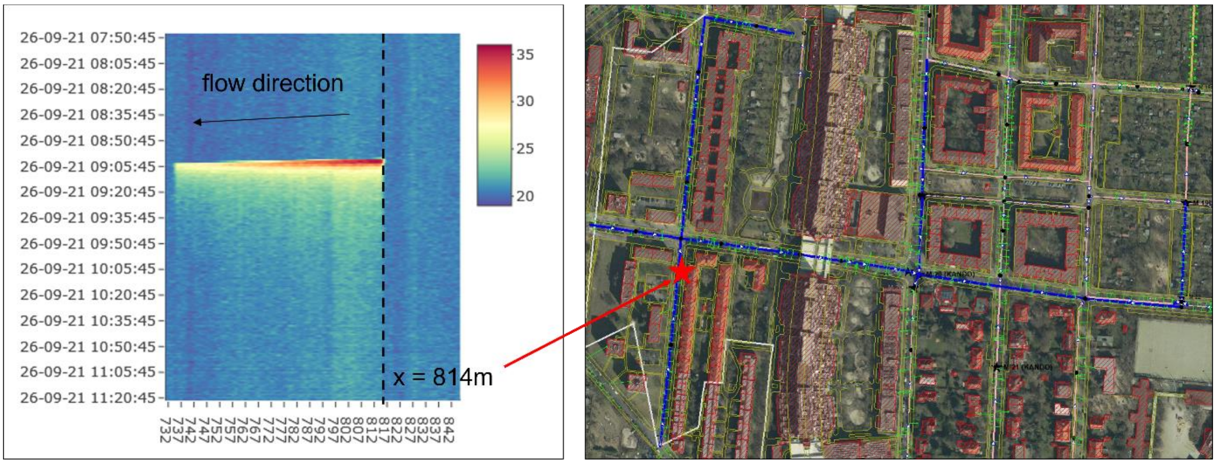

Figure 16: Example of DTS monitoring results (left); corresponding location of the suspected illicit connection (right)

At that location in the storm sewer inflows were observed on 55 occasions in the five-week monitoring period, indicating an average of about two spills per day. Typically, the first spill began early in the morning (around 06:00), except for the weekend (08:00-10:00). The number of discharges as well as the observed pattern correspond well to a typical household

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pattern. The illicit connection has been confirmed in the field by inspection of the stormwater house connection in cooperation with the caretaker of the building.

5.3.2. KPI 2: OPEX ratio

This KPI compares the costs of application of CCTV and DTS, expressed per 1.5 km of inspected sewer length. For DTS the costs comprise:

- installation and removal work: 24.000 €
- equipment rental: 20.000 €
- organization, data analysis and reporting: 20.000 €

These values are based on actual costs for the Fennsee project. Typically, project costs are strongly determined by project organization, scale of the project, and purchase or rental of equipment.

For CCTV the costs comprise 18.000 €. The value is based on average costs of 12 €/m sewer for CCTV inspections in Germany. Consequently, the OPEX ratio assessment yields

$$KPI\ 2 = OPEX\ ratio = \frac{cost_{DTS}/length_{DTS}}{cost_{CCTV}/length_{CCTV}} = \frac{(24000€+20000\ €+20000\ €)/1.5\ km}{18000€/1.5km} = \frac{42666\ €/km}{12000\ €/km} = 3.55$$

This is a 3 ½ times increase in OPEX. Considering the costs, it should be noted that both methods (DTS and CCTV) yield different results associated with these costs, see KPI 1 'IC detection'.

5.4. Return on experience

An important aspect in the realization of a DTS monitoring set-up is the connection between the fiber-optic cables in the sewer system and the DTS-unit located in a storage cabinet above ground (see Figure 15, right). Typically, the access to the sewer system is realized via a sewer manhole that allows easy and safe access, e.g., via a fenced-off manhole at a parking lot or another location with no or only little traffic. In the Berlin Fennsee area, however, no such manhole was available as all storm sewer manholes were located in the middle of streets, see Figure 17.

As an alternative, a connection was realized via the storm sewer connection of an individual building. For this, the accessibility of the house connection was first tested using a manual sewer pushing rod. Then, the fiber-optic cables were pulled through the house connection pulling the rod backwards. This way, two fiber-optic cables were successfully installed via the house connection.

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Figure 17: Storm sewer manhole located in the middle of the street (right); preparations to realize access to the sewer system via house connection (left).

6. DS14: Low-cost temperature sensors for real-time combined sewer overflow and flood monitoring

6.1. Digital solution

The solution DS 14 consists of low-cost sensors installed in specific locations of each CSO structure that detect sewage discharge events. The sensors are connected with a visualisation platform that allows monitoring of what happens in each CSO point. The solution is able to monitor and send alarms from a high number of CSO points, thus providing water utilities with crucial information on the performance of their sewer networks and detecting critical contamination points (see Figure 18).

Figure 18: DS14 concept, an example of online device and web platform interface.

DS14 is based on temperature measurements and on the principle that, in a CSO event, the temperature of discharged wastewater is significantly different from the ambient temperature in the sewer atmosphere. Thus, the strategic location of temperature sensors in overflow structures can efficiently detect the temperature changes and correlate them as discharging events. In the case of dry weather, the sensor measures the air phase whereas, in the case of CSO, the discharged storm and wastewater is measured. The start and end of a CSO event can be determined via the merging of measured temperatures values in both points of the overflow structure.

DS14 has two versions: offline and online. The offline version consists of two temperature loggers installed in the CSO point: one at the overflow crest which measures air temperature during dry-weather conditions and water temperature when the overflow crest is submerged in case of a discharge, and another logger constantly submerged into the main sewer channel which measures wastewater temperature. The online version includes two temperatures sensors, one capacitive sensor and one water level sensor for extra-validation of CSO occurrence to avoid even more the number of false positives. It is built with high-capacity Lithium-ion batteries to maximize its lifetime which is around two years, depending on the installation conditions, the number of sensors activated and the number of transmissions. Monitoring information is sent to a web platform either by GPRS M2M communication nodes or LoRaWAN, a low-energy consumption protocol that uses the EU868 standard. In the platform, utilities can visualize the location and status of CSO points of their sewer network.

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6.2. Demo description

DS14 has been tested in two demo sites: Sofia (Bulgaria) and Berlin (Germany). Sofia was selected as it has a large number of CSO structures with, to date, no monitoring at all. Hence the demo project provides great additional knowledge on the location of the major emission points and helps to locate suitable mitigation measures in the future. Berlin was selected as there are already some water level sensors installed, that can be used to validate the new low cast sensors. Further, a hydrodynamic model of the catchment exists, which can be used to demonstrate the benefit of a large number of low-cost sensors over a few costly water level sensors in terms of model calibration.

In Sofia, the catchment area of the city has a total surface of 13,640 ha. It is divided into six main sub-catchments: Kakach, Suhodolski, Vladayski, Perlovski, Slatinski and Trunk, named after the main rivers crossing the city. It is a combined sewer system with the main sewer collectors located on the two sides of the rivers. Under dry weather conditions, wastewater is drained to the Kubratovo wastewater treatment plant mostly by gravity. Kubratovo WWTP treats 300,000 m^3/day, which is 70% of its full capacity. Overflows structures in Sofia are designed to discharge a six-times diluted domestic outflow and they are inspected twice a year by the specialist field team of Sofiyiska Voda (SV). A total of 232 CSO structures are present and help to unload the sewer system during rain events. Within DWC, 22 CSO points have been monitored, 10 of them with offline sensors and 12 with online sensors. The monitoring campaign expanded from October 2020 to the end of the project (~ 2 years in total).

In Berlin, DS14 is installed in its biggest combined sewer catchment “Wilmersdorf” located in the central-western part of the city. The catchment has an impervious area of 921 ha, a total area of 1,651 ha and drains sewerage of approximately 265,000 inhabitants. The settlement structure shows a high variety in population density with little industry and is, therefore, representative of municipal wastewater in Berlin. During dry weather conditions, around 40,000 m^3 of wastewater are generated each day and pumped to the wastewater treatment plant. Maximum pumping capacity during wet weather conditions is twice the peak dry weather flow (2 x 750 L/s = 1.5 m^3/s). Excess water is discharged via 19 overflow crests which are connected to the receiving river via three CSO outlets. Within DWC, 18 overflow structures of the Wilmersdorf catchment are being monitored, 9 of them with online sensors and 9 with offline sensors. The monitoring campaign expanded from October 2020 until the end of the project (~ 2 years in total).

6.3. Assessment of the digital solution

The benefits of DS14 have been assessed via six defined performance indicators (KPI). The results are summarised in Table 8. Details on considered input data as well as calculations are given in the subsections below.

Context of the results obtained: KPI’s were calculated based on data obtained during the monitoring periods between September 2020 - September 2022 for offline sensors and September 2021-October 2022 for the online sensors. As explained in previous reports, the

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Covid situation and other technical and practical situations had an impact on the deployment and functioning of the online sensors. These unexpected scenarios prevented to obtain sufficient information and quality-datasets to rigorously calculate KPI's 5 and 6.

Table 8: Overview table of KPI assessment for measurements in the year 2021.

KPI	Short description	Quantification
1. Number of additional CSO events detected	Number of additional CSO events detected since DS14 was applied.	Sofia: ≈30 CSO events/catchment-year Berlin: Same number of CSO events (15 events) detected by level sensors preinstalled but in a higher number of locations.
2. Detection accuracy for CSO frequency	The difference in the number of CSO events with other monitoring systems and DS14.	Sofia: Not applicable. No other monitoring systems were installed in the selected catchments. Berlin: Same number of CSO events (15 events) detected by DS14, when compared with level sensors preinstalled.
3. Detection accuracy for CSO duration	Time of CSO discharging detected with DS14 and other monitoring systems.	Sofia: ≈140h of yearly CSO average duration detected by DS14. Comparison with other monitoring systems was not possible. No other monitoring systems were installed in the selected catchments. Berlin: Similar time of CSO duration comparing DS14 and level sensors preinstalled. Level sensors: 107h of overflow. DS14: 116h of overflow.
4. Capex Reduction	Reduction of capital costs related to CSO monitoring	Significant capex reductions compared to other monitoring systems available in the market. DS14 Offline:77-92% reduction in costs/unit. DS14 Online:46-78% reduction in costs/unit.
5. Opex Reduction	Reduction of operational costs related to CSO monitoring.	Opex reduction calculation could not be completed due to operational limitations with the online devices.

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6. Increase in model accuracy	Increase in hydraulic model accuracy due to data provided by the CSO sensors	Could not be completed due to time limitations with the temperature sensors data.

6.3.1. KPI 1: Number of additional CSO events detected.

KPI 1 accounts for the number of additional CSO events detected since the deployment of DS14. As expected, there has been an increase in the CSO events detected in Sofia, where no CSO detection systems existed to date, and a confirmation of the number of events occurring in Berlin Wilmersdorf catchment, where CSO detection instruments were originally in place. Overflow events were calculated from the temperature data obtained from the sensors and compared with rainfall data for each structure and catchment where the CSO structure was located.

Sofia: Sofia has a total of 232 overflow points and DS14 was implemented in 22 CSO structures spread in 6 sub-catchments of the city. Results obtained showed that in 2021, 132 rain events occurred and produced ≈30 CSO events all over the city. In CSO points *PR01KAK&PR07LSU*: 30 CSO events occurred, in *PR11GAR&PR18LSU*: 29 CSO events, in *PR01DSL&PR23TR2*: 35 CSO events, in *PR13DSL*: 30 CSO events and in point *PR46LVL*: 37 CSO events. In the same period, 2 CSO structures showed a significantly higher number of CSO's. 71 CSO events were detected in *PR15TR2* (Perlovskisubcatchment) and 66 CSO events in *PR30LVL* (Vladayski subcatchment). Sofiyska Voda confirmed that those CSO structures had a lower overflow crest and tend to accumulate a lot of debris which means that could spill more frequently, even in very light rain conditions. Information obtained helped to identify some of the most critical structures in terms of discharge of sewage in Sofia. This information was very important for Sofiyska Voda as they had, for the first time, data about the geographical distribution of overflowing that allowed them to start designing adequate actions accordingly.

Berlin: In Berlin, 18 overflow structures of the Wilmersdorf catchment were monitored with DS14. Results obtained showed around ≈15 overflow events from a total of 57 rain events in 2021. The Wilmersdorf catchment had in place 2 water level sensors and those were used to compare and validate the results of DS14. For instance, the level sensor installed in Rue19 showed and occurrence of 15 CSO events and the DS14 offline sensor installed nearby showed the same number of CSO's. That indicates the performance of DS14 was as good as other methods previously deployed in the catchment. No additional overflows were detected. An additional benefit of DS14 is the higher number of structures monitored compared to the low number monitored with level sensors. That means we were able to account for the geographical distribution of each CSO event. Figure 19 below presents the overflows produced by a rain event on the 23/12/2021 (15.2 mm rain in 23.6 hours). The red rectangles show the locations where there was as spill of sewage, which in this case was in 10 different points.

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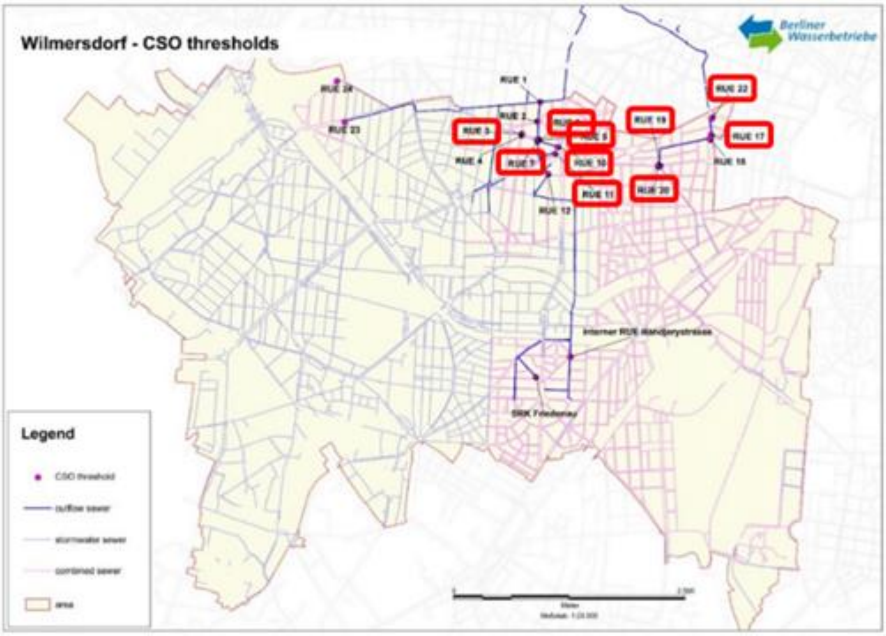

Figure 19: Geographical distribution of the CSO event occurred on the 23/12/2023 in Berlin's Wilmersdorf catchment.

6.3.2. KPI 2: Detection accuracy for CSO frequency-occurrence

KPI 2 consist of a comparison between the number of CSO events detected with other monitoring systems installed and DS14.

Sofia: KPI 2 could not be calculated for Sofia as DS14 is the first CSO monitoring equipment deployed in the different catchments of the city, so no reference values were available.

Berlin: The Wilmersdorf sewer system was equipped with commercial water level sensors (external to the project) in 2 locations nearby overflowing structures (Rue 19 and Rue 20). Water level sensors measured the depth of the water surface in the sewer and, knowing the depth of the overflow crest in each structure, level data can be used to estimate the occurrence of overflowing. As explained above, DS14 and water level sensors installed in nearby locations showed a very similar behaviour in terms of number of CSO's detected, 15 CSO's in 2021. As an example, Figure 20 below presents the CSO occurrence detection in RUE20 from February to July 2021. Rainfall data (red line) showed a very strong correlation with the increase of the water level in the sewer (blue line). According to water level measurements, on 4 occasions the water reaches the overflow height, fixed at 32.5m (dashed green line). Results from DS14 in *RUE20* (red dots) detected also total of 4 overflow events in the same period.

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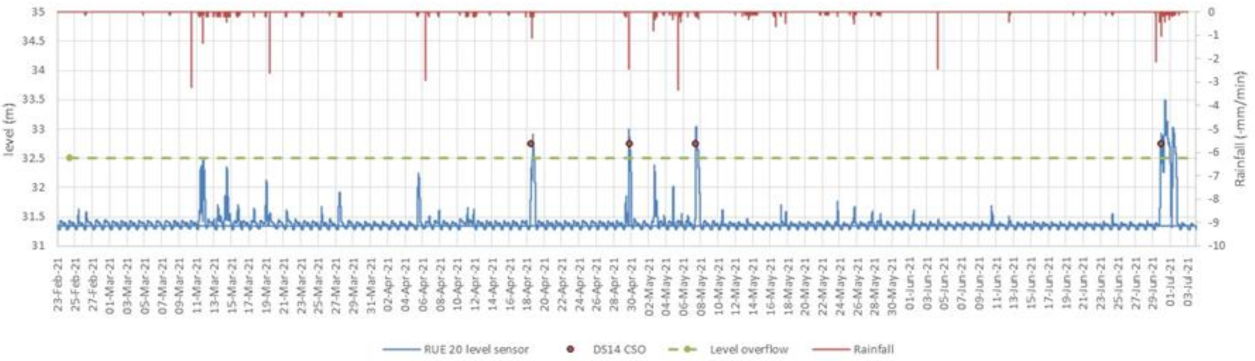

Figure 20: Rainfall, water level and DS14 corresponding to RUE20 CSO point in Berlin.

6.3.3. KPI 3: Detection accuracy for CSO duration

KPI 3 consists of the time difference between the duration of CSO events detected by DS14 and the duration with other monitoring systems. KPI 3 was calculated according to the following expression:

$$KPI\ 3 = \sum Time\ of\ overflows\ detected\ by\ DS14/mm\ rainfall \cdot time - \sum Time\ of\ overflows\ detected\ with\ other\ systems/mm\ rainfall \cdot time$$

KPI 3 values higher than 1 indicate the higher time of sewage discharged detected by DS14 compared to other methods. KPI 3 can be calculated either for a single CSO structure or for a catchment.

Sofia: KPI 3 could not be calculated for Sofia as DS14 is the first CSO monitoring equipment deployed in the city, so no reference values were available. However, it is worth mentioning that the duration events detected in 2021 lasted ≈145h (≈30 CSO's from 122 rain events).

Berlin: In 2021, water level sensors installed in *Rue 19* detected a total of 107 hours of CSO's for the whole year. In the same structure and same period, DS14 offline sensors detected a slightly higher number of duration discharges, 116 h. This corresponded to a deviation of +7h (+8%) from the water level reference measurements. These differences are most likely explained by the delay of DS14 to recover normal temperature conditions of the sewer at the end of CSO events, which could lead to a small overestimation of the spilling time. Rue 19 was the most overflowing structure in the whole catchment, so the overall Wilmersdorf numbers were very similar to those observed in this structure. DS14 and water level sensors data was crossed with rain records to identify and discard potential false positive CSO events.

6.3.4. KPI 4. Capex reduction

Capital costs were calculated based on the cost of an individual sensor and its installation. The commercial cost estimated for DS14 online version was 1388 €/unit while the cost for DS14 offline version was 459 €/unit. Cost of commercial water levels in the German, Bulgarian and Spanish markets was used to calculate the difference in the capital expense of sensors. Table 10 below presents the cost of the commercial sensors and the % reduction compared to DS14.

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Table 9: Cost comparison and % reduction of DS14 online and DS14 offline compared to other monitoring methods commercially available.

Water level sensor cost Provided by BWB and SV	**DS14 Online:** Cost 1338 €/unit	**DS14 Offline:** Cost 459 €/unit
Germany Level sensor. Cost 6500 €/unit	78%	92%
Bulgaria Level sensor. Cost 4638 €/unit	70%	90%
Spain Level sensor. Cost 2500 €/unit	46%	77%

DS14 is significantly cheaper than usual water level meters on the market. The cost of the DS14 online version is 46-78% lower than other methods while the cost of the offline version is 77-92% lower. That means that for a fixed budget, a higher number of CSO structures could be monitored using DS14. However, the DS14 online version is still in the prototype stage with technical problems to be addressed before being considered commercially ready. Also, DS14 offline version is ready to be marketed but its lower cost is due to is limited features such as no real-time alarms and manual download of the data.

6.3.5. KPI 5. Opex reduction

Operational expenses could not be calculated for DS14. DS14 online prototypes operated only for a limited time at the end of the project. It was deemed not sufficiently representative to establish its operational costs. This was due to delays in its construction, its lengthy deployment and unexpected technical problems that increased the time dedication of BWB and SV field teams to repair and ensure its functioning. It is assumed though that if working properly, the DS14 online costs would be in the same order of magnitude as the other methods such as water level meters. BWB estimated the average operational expenses of the level sensors as 1750 €/year. With regards to the DS14 offline sensors, Sofiyska Voda current practice is to proactively check the offline CSO points monthly, which increases its operational expenses.

6.3.6. KPI 6: Increase in model accuracy

KPI 6 consisted on the increase in hydraulic model accuracy due to data provided by the CSO sensors. KPI 6 could not be assessed due to a delay in obtaining reliable data on the temperature sensors, necessary for the hydraulic calibration. In an additional study, it was shown, that the calibration of a dynamic rainfall-runoff-routing model using fictitious temperature data achieved the same accurate results as a conventional calibration using water level data. ICRA and KWB agreed to continue this task beyond the end of the project.

6.4. Return on experience

Return of experience from city partners point of view: The return of experience from both SV and BWB has been overall positive. They highlighted the ease of installing the sensors, both for the online and offline versions, even for inexperienced operational teams and the simplicity in maintenance tasks such as replacing batteries and cleaning sensors. They also mentioned the user-friendly interface of the web platform designed for uploading and

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monitoring the overflow events. On the things-to-improve side, they pointed out that hydrodynamics of the offline sensors could be improved to avoid the loss or malfunctioning of those sensors due to shear and strain produced by wastewater. Also, an increased battery life of the sensors would be very helpful to reduce the frequency of manhole maintenance activities for operators. The technology providers, ICRA and IoTsens, have already addressed these issues and the updated sensors are sent to both Berlin and Sofia. SV and BWB also suggested a few modifications in some functions in the monitoring platform (e.g., data uploading) which have also been addressed.

Return of experience from the technology providers point of view: From ICRA and IoTsens, the return of experience is also largely positive. DS14 has been confirmed as a good-valid solution for mapping CSO events in a city, which fits in the needs of SV and BWB, and potentially, many other utilities in the world. The regular feedback from SV and BWB has been very helpful to expand from the initial concept of DS14, identify its limitations and apply upgrades such as connection to rain gauges, communication protocols, etc. The greatest challenge was related to the operational problems with testing, the construction, the deployment of the DS14 online sensors under pandemic conditions. Field teams from SV and BWB were very helpful to resolve these limitations, but still, a limited operation time of the DS14 impacted the volume and quality of results within the study.

The main challenges for the last months of the project were to address limitations such as the reliability of the online prototypes, the suboptimal raw data sets, and the improvement of CSO event detection algorithms. Despite those setbacks, we were able to address some of these limitations. It has to be mentioned that DS14 is not mature enough to hit the market. Nevertheless, its development will continue beyond the project in close contact with SV and KWB.

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7. DS15: Smart sewer cleaning system with HD camera and wireless communication

7.1. Digital solution

The removal of sediments and blockages from sewer pipes represents a major expense for sewer operation and maintenance. However, sewer cleaning is indispensable in order to avoid odor and corrosion of sewer pipes and conserve their hydraulic capacity. Usually, cleaning is done blindly, i.e., separated from the inspection process, which leads to unknown and often unsatisfactory cleaning efficiency. To overcome this lack of coordination between cleaning and inspection, a combined sewer cleaning and inspection system is tested as DS15. The system called XPECTION consists of a high-pressure cleaning nozzle and a high definition (HD) camera that transmits the video signal from the nozzle to the inspector's tablet by wireless connection. The technology can be applied to high-pressure sewer cleaning trucks and allows for continuous monitoring of the quality of the cleaning and further detecting and observing major defects of the sewer pipes. Figure *21* visualizes the main components of DS15.

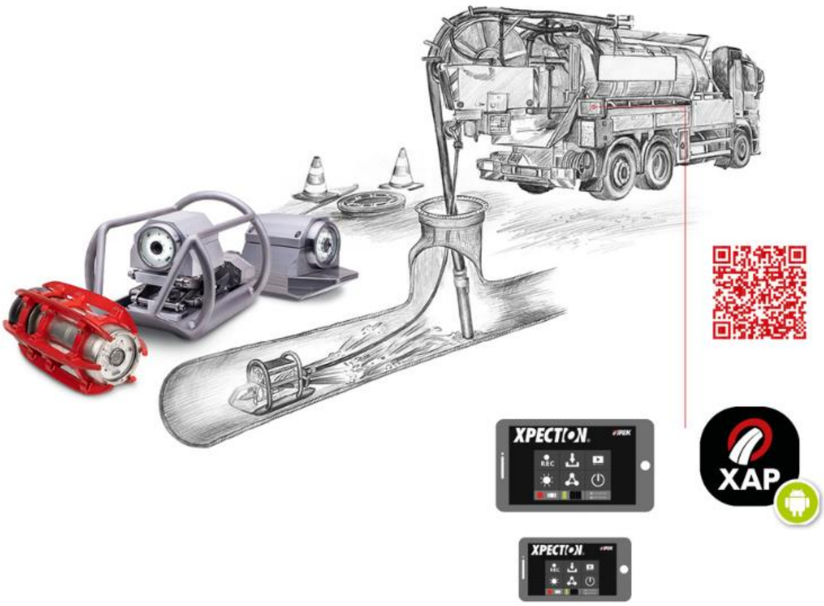

Figure 21: XPECTION device for smart sewer cleaning (DS15) consisting of the cleaning nozzle, the inspection camera and a control panel for visualization.

7.2. Demo description

The solution is demonstrated in the cities of Sofia, Bulgaria, and Berlin, Germany, during nine-month-monitoring campaigns.

In Sofia, around 10 km of sewer pipes were selected for demonstration. These pipes are either located in areas known to have frequent operational problems or are most likely currently subject to acute blockages in the combined sewer. The selected pipes have a circular or egg-shaped cross section and a diameter/height between 200 and 800 mm. In addition to the cleaning process, the videos from XPECTION increase the inspected length of sewer pipes and

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give additional information on the structural pipe condition. For the assessment of its performance, DS15 will be compared to the cleaning with a standard nozzle ("blind" cleaning). In total, 2.3 km of the designated 10 km of pipes have been inspected by the end of the project.

In Berlin, the demonstration of DS15 is part of the standard operational routine and includes storm, sanitary and combined sewer pipes. Four different use cases are distinguished: (i) standard cleaning, (ii) pre-cleaning for CCTV inspection, (iii) observation of known sewer defects and (iv) visual control of obstacle removal in sewers. In parallel to the demonstration of DS15, pipes are cleaned and inspected with standard techniques ("blind" cleaning, panorama video camera). For the performance assessment of DS15, monitoring time, effort and benefits for each operational working step in the daily working routing are compared for the different use cases. Table 10 gives an overview of the field operations in the demo in Berlin.

Table 10: Overview of the current status of the operations

	XPection	Current practice
Standard cleaning	29 operations / 44 sewers	44 operations / 44 sewers
Pre-cleaning for CCTV	5 operations / 5 sewers	5 operations / 12 sewers
Observation of known damages	24 operations / 25 sewers	4 operations / 4 sewers

7.3. Assessment of the digital solution

During the first part of the demonstration, DS15 has proven to be a helpful additional tool for the cleaning teams in both Sofia and Berlin. DS15 has been particularly useful for cleaning and inspection of non-circular pipe cross sections, where no other visual technology has been applied. The solution is a good tool to find hidden connections and manholes, especially, in small diameter pipes, where CCTV crawler could not be applied.

For each usecase, the operational workflow was described with respect to the current practice and usage of DS15 in detail. The differentiation of working steps such as preparation at the workyard, preparation at the place of action, execution of the application, evaluation of the action and post-processing is the necessary basis to compare qualitatively and quantitatively the effort and benefits of the new technology in relation to the current practice. Beside the time needed for each working step, special issues like usability, disruptions, video quality and additional findings were monitored.

The benefits of the solution have been assessed via predefined performance indicators (KPIs) (see

Table 11). The results are summarised and details on considered input data as well as calculations given in the subsections below.

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Table 11: Overview table of KPI assessment

KPI	Short description	Quantification
1. Cleaning effort	Time needed for the cleaning steps (mounting the equipment; cleaning; reinstallation) using digital solution XPECTION (DS) compared to Standard Cleaning (SC)	$= \frac{average\ cleaning\ time\ DS\ [min]}{avarage\ cleaning\ time\ SC\ [min]} * 100\% = \frac{68min}{30min}$ *100% = 227%
2. Inspection efficiency	Related to: 1.1. Observation of known damages 1.2. Finding new damages	Number of defects
3. Financial value	1.1. CAPEX (XPECTION compared to current techniques: Blind nozzle; Telescopic mirror (camera); CCTV) 1.2. OPEX (XPECTION compared to current techniques) • Personal costs • Travel costs	Expenses, €

7.3.1. KPI 1: Cleaning effort

This indicator compares the execution time of the individual steps in the process of sewer cleaning when performed in a classic way, with a blind nozzle, and using the video nozzle.

Table 12: Representation of cleaning effort calculation. Average values (in min) from demo in Berlin and Sofia are taken.

	Xpection	Standard Nozzle
Number of operations	29 BWB + 15 SV = 44	44 BWB + 15 SV = 59
Preparation time [min]	15	8
Cleaning time [min]	39	17
Reinstallation and evaluation [min]	14	6
Total time [min]	68	31

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7.3.2. KPI 2: Inspection efficiency

The indicator evaluates the ability to detect structural defects along the sewer sections using the appropriate cleaning equipment and/or visual control.

Table 13: : Representation of inspection efficiency is calculated from 36 operations with XPECTION in Berlin and Sofia, 11 "blind" cleaning operations in Sofia and 4 operations with electronic mirror in Berlin.

	XPECTION	Standard Clean	Electronic Mirror
Number of operations	36	11	4
Damages found	42	1	2
Percentage	117 %	9 %	50 %

7.3.3. KPI 3: Financial value

CAPEX

The calculations in Table 14 compare the capital costs of cleaning and video inspection of the cleaned sewer sections. It is accepted that when cleaning, we need a cleaning truck and it is a constant in cleaning operations(A). In order to make smart price-quality decisions, the table also describes the added value of each of the combinations.

OPEX

The operation and maintenance team of Sofiyska voda AD uses a suitable type of sewer truck for cleaning works. To perform a video inspection, a video inspection team with a video equipment comes to perform the recording after cleaning the pipe. The XPECTION demonstration showed that in order to use the technology, it is needed qualified staff to work with it, delivering it to the site in a separate vehicle. Thus, the use of XPECTION is not distinguished as an operational cost from the operational cost of video recording of any type. There is no need for the CCTV crawler team to perform with XPECTION. It can be done by a sewer inspector, so that the CCTV crawler team is free for other inspections.

In common practice an increase of OPEX can be observed when cleaning quality occurs not to be good enough, and there is need of repetition of the cleaning and the visual control. In this case, we have twice as high operating expenses.

At the end of the project the XPECTION Lite technology was presented from IPEK to SV. XPECTION Lite has less components than XPECTION. Considering the technical characteristics presented there, probably no additional team to accompany the cleaning team would be needed. This will lead to OPEX reduction due to field visit by the cleaning team only.

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Table 14: CAPEX values are rounded values without VAT, taken from Sofia's last delivery contracts. The price of XPECTION and XPECTION LITE is provided from IPEK.

Type of cleaning and visual control	Equipment for:	Price, Euro	Added value
Standart Cleaning	Cleaning Truck(A) + Standard nozzle(B)	(A) + (B): from 100 to 850, depending on the size of the nozzle	Only cleaning
Standart Cleaning + Visual control of telescopic camera	Cleaning Truck(A) + Standard nozzle(B)+ Inspection team with telescopic camera(T)	(A) + (B) + (T):16500euro	Cleaning; Live quality control of the cleaning; Live visual control of the structural condition of 20-30% the pipe
Cleaning with XPECTION	Cleaning Truck(A) + Inspection car with XPECTION nozzle(X)	(A) + (X):37800euro	Cleaning; Live quality control of the whole cleaning length; Live rough visual control of the structural condition of the pipe
Standart Cleaning + Visual control of CCTV robot camera	Cleaning Truck(A) + Standard nozzle(B)+ Inspection team with CCTV robot camera- C	(A)+(B)+C: 261000euro	Cleaning; Live quality control of the whole cleaning length; Live detailed visual control of the structural condition of the pipe; Coding of defects; Export CCTV data in different formats
Cleaning with XPECTION LITE(from documentation)	Cleaning Truck(A) + XPECTION LITE nozzle(no inspection car required) (L)	(A)+(L): 11000euro	Cleaning; Quality control of the whole cleaning length; Rough visual control of the structural condition of the pipe.

7.4. Return on experience

For Sofia and Berlin, demonstration of the solution was provided and served as the time to get used to the technique and evaluate the advantages and the disadvantages of its application.

DS15 has proven to be perfect additional tool for the cleaning team, used for the several use-cases, where the CCTV was not applicable:

- Cleaning and inspection of Egg-shaped profiles;
- Inspection of the structural condition of small diameters;
- Finding and observation of pipe defects;
- Finding connections and hidden manholes.

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Although the usage of DS15 is resulted in additional time and effort of the operational team compared to the routine practice, the video quality is very good and gives good information about pipe's structural and operational condition. The huge benefit in using DS15 is this good video instead of issuing a work order and performing a new CCTV inspection. Observations, where a picture inside the sewer is needed, are actually carried out with an electronic mirror (or telescopic camera) and often it is hard to see the point of interest, if it is more than 10m away from the manhole.

During long inspections the transmission provided by DS15 is not so good but the nozzle keeps the video and it can be downloaded, later, in the office. In Egg-shaped cross-sections the transmission is twice as a good. The various cleaning nozzles are robust and heavy, as they should be to work in the sewer system. The most comfortable one, for the small diameters was the "Brendle Duebre roudjet nozzle". The software is user-friendly. The menus and buttons inside are logical and easy to navigate.

Figure 22: A iPEK XPECTION device for smart sewer cleaning.

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Figure 23: A iPEK XPECTION device for smart sewer cleaning in usage in Sofia.

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8. DS11: Sewer flow forecast tool box

8.1. Digital solution

The integrated management of the sewer network and the wastewater treatment plant (WWTP) is important to minimize CSO emissions, WWTP bypasses[8] and pollutant loads emitted via the WWTP. To better control the filling and emptying of retention basins as well as treatment processes at the WWTP, forecasts of the inflow to the drainage system and the WWTP are required. However, inflow forecasts derived from simpler methods are typically highly uncertain and only have relatively short forecast times.

The goal of DS11 ("Improved machine learning (ML) sewer inflow forecast") is to enhance the performance and accuracy of the inflow forecast to the wastewater treatment plant (WWTP) so that control strategies between the sewer system and the WWTP can be optimized and CSOs and bypasses of untreated sewage to receiving waters can be further reduced. The solution, which comprises routines for data processing and the ML model applications, will provide short- and medium- time forecasts of inflow timeseries and probability of rain, respectively. The short-term inflow forecasts with lead times up to three hours will help to guide the control decisions at the WWTP and prepare for high flow conditions during rainfall. The medium-term rain probability forecasts with lead times up to 36 hours enable more flexibility for emptying the storage basins compared to the current practice, in which all basins must be emptied within 24 hours[9] after the rainfall. Retention and slow emptying are relevant when runoff exceeds the biological treatment capacity at the plant or the actual biological capacity at the plant is lower than the design capacity due to low temperatures and/ or after long lasting rain events.

The short-term forecast is based on a point prediction ML model which provides a unique flow value for each time instance of the forecasting period. The medium-term forecast is a probabilistic ML model, which also allows to reveal uncertainties in expected rainfall, respectively inflow. Both models are part of a software package, that also includes different components for data processing, deployed in a real-time environment.

Automatic data services have been set up to ensure near real-time updating of the database hosted on a cloud service, enabling easy retraining of the model on new data. The ML model will produce forecasts to be used for the decision support system (DSS) and real-time control algorithms (DS12) for both dry and wet flow conditions. Predictions made for the end of October 2021 are shown in Figure 24. The input data arrives from different sources/locations. One or more of the sources are occasionally interrupted. A total of five combinations of missing data can occur and to produce continuous inflow predictions, five different ML models

[8] Bypass is a term used at the WWTP for water that bypasses the biological treatment step at the WWTP and is led only mechanically cleaned to the recipient.

[9] In Denmark the rule of thumb for emptying retention basins is 24 hours. The arguments are, that otherwise the basin will be full when the next rain events hits the catchment and increased biochemical reactions in the retention basins taking place.

have been trained and deployed to account for missing data instances. The five situations are presented in the figure below, and e.g., “NoNovafos” means no data from Novafos.

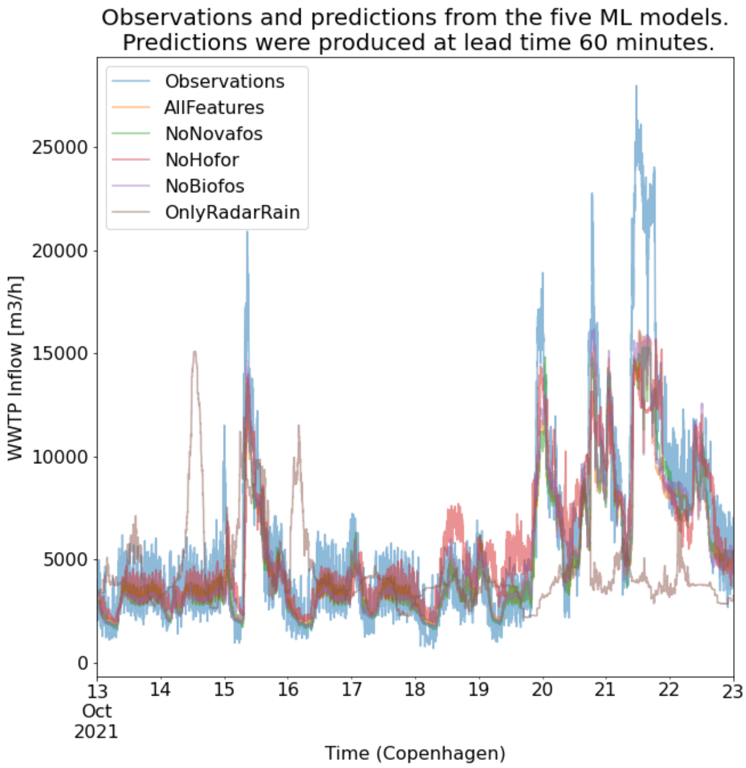

Figure 24: To make the machine learning predictions more robust, five models with different inputs were created. This figure shows observations and predictions from the five different ML models.

We have monitored the “uptime” for the different data suppliers, HOFOR, Novafos and BIOFOS. The records cover the period 11. October 2021 to 30. October 2022. During the 12-months period, data have been missing from Novafos. This is rather unfortunate, as a major part of the catchment is within the territory of Novafos. The stats are listed in Table 15.

Table 15: Overview of sensor data availability for the ML routine during a 12-month period

Sensor availability	**% of uptime**
All sensor data	14
No data from Novafos	65
No data from HOFOR	0
No data from BIOFOS	0

The total uptime of the ML routine is 83% of the calendar time, or in other words, in 17% of the time the ML has been non-active for different reasons, like server repair, sensor

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maintenance and lack of attention from the data owner. Only in 14% of the overall time, all data sources have been available for the ML forecast.

The medium-term forecast is provided as a visualization of the precipitation forecast. The original plan was to develop an ML model to predict the WWTP inflow based on Numerical Weather Prediction (NWP) data. When the trained prediction ML model was ready to be deployed in real time, we found that the data provider no longer provided the necessary NWP data. This spawned discussion of possible solutions, through which it was realized that visualization of the raw precipitation forecasts would be more useful for coordination of basin emptying in the catchment. The development of the medium-term forecast model was completed in 2021.

8.2. Demo description

The solution is tested in the catchment area Damhusåen in Copenhagen. The catchment's sewer system, operated by three different sewer operators (HOFOR, NOVAFOS, Frederiksberg Utility) is mainly combined (85%), with ca. 200,000 m³ established storage volume and ca. 86 CSO structures across the catchment, representing 45% of all CSO structures in BIOFOS total catchment area. Stormwater runoff and wastewater is primarily transported by gravity and control options are limited.

The ML model for short-term forecasting of inflow to the WWTP has been trained using real-time volume, water level and flow sensor data from the sewer system and weather radar observations. The ML model produces forecasts to be used for the decision support system (DSS) and real-time control algorithms (DS12) for both dry and wet flow conditions. The short-term inflow prediction model is comprised of two sub-models, as shown in Figure 25.

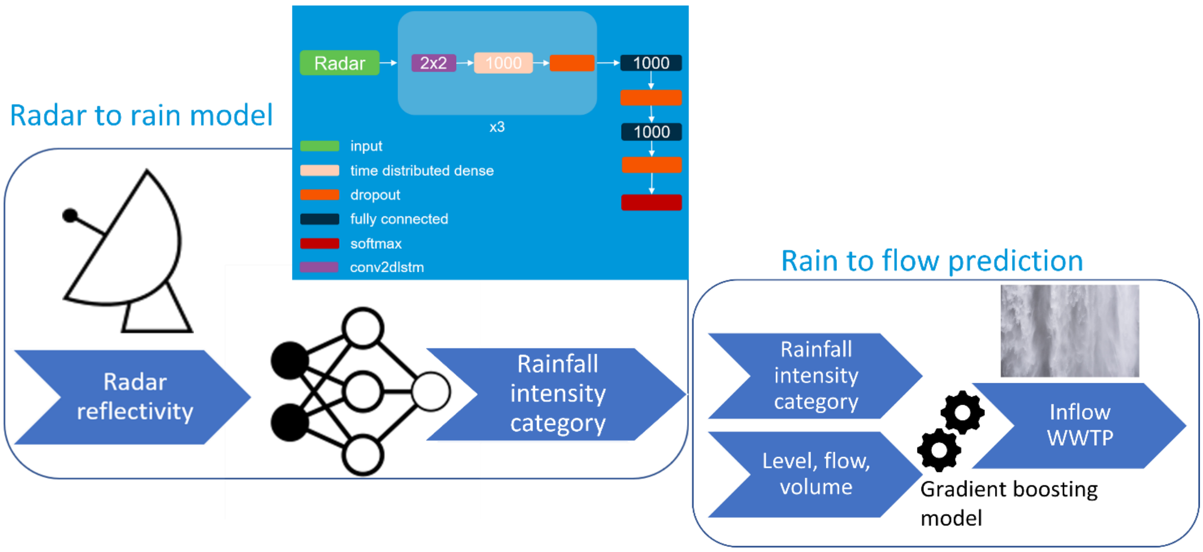

Figure 25: WWTP inflow prediction composite model.

The first sub-model translates the weather radar image to a rain intensity category. The output from the first sub-model is given as input to the second sub-model, which predicts the inflow. For the first sub-model, we experimented with a range of deep learning model architectures, including different convolutional and recurrent neural network configurations, cost functions,

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observation weights, and optimizers. The architecture settled upon is shown in Figure 25. For the second sub-model, we compared random forests, neural networks, Gaussian processes, multivariate linear regression, and several variants of gradient boosting, including probabilistic versions. These were evaluated using the root mean square error (RMSE), and the gradient boosting model as implemented in the LightGBM package outperformed the other models. When retraining the model, several runs with different hyper-parameter settings are fitted on training data. Validation data is used to find the best model, and that model is deployed if it outperforms the currently deployed model on test data.

We evaluated deep learning models for medium-term inflow forecasts based on NWP data using archives of relatively high-resolution historical data of ensemble forecasts. This data type is no longer available, so the focus of this work has shifted to visualization of probabilistic precipitation forecasts. Through dialogue sparked by the unavailability of the original data, we have uncovered that medium-term probabilistic precipitation forecasts are likely to be of higher value than medium-term inflow forecasts for planning purposes at the WWTP and upstream utilities.

8.3. Assessment of the digital solution

The benefits of the solution have been assessed via three defined key performance indicators (KPI). The results are summarised in Table 16. Details on considered input data as well as calculations are given in the subsections below.

Table 16: Overview table of KPI assessment

KPI	Short description	Quantification
1. Accuracy for short-term inflow forecast during wet weather - 3h	Accuracy of the new inflow forecast compared to the existing inflow forecast based on a linear reservoir model, operational at the WWTP and observed data. Accuracy is quantified via mean error (ME) and root mean square error (RMSE) with regards to observations. Different forecast lead times up to 2 hours are considered.	35-42 % for lead times between 30 and 120 min; The achieved results are reported in 8.3.1
2. Accuracy of forecast time for dry weather – 36 h	The KPI evaluates the accuracy of dry weather forecasts for the next 36h by comparing forecasts with registered rain data respective to the lead times.	Percent [%] categorized as correct dry weather forecasts The achieved results are reported in 8.3.2
3. Reduction of wrong automatic switching between dry and wet weather operation at the WWTP	The KPI evaluates whether the new inflow forecast model is better than the operational inflow forecast model, thereby reducing the wrong switches between dry and wet weather operation at the plant.	Count; percent [%] The achieved results are reported in 8.3.3

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If deviations between measured and forecasted flows assume both negative and positive numbers, the mean error expression does not provide any insights into accuracy of the forecast. This has been the case in this project, for which reason the KPI for ME is not calculated. The KPI for the RMSE is listed in Table 17 in Section 8.3.1.

8.3.1. KPI 1: Improved forecast during wet weather

The performance / accuracy of the new inflow forecasts and the current forecasting system is calculated with regards to inflow measurements at the WWTP and the existing inflow forecast "STAR". Performance is evaluated for different forecast times (30, 60, 90 and 120 minutes) as the mean error (ME) and the root mean square error (RMSE).

Two performance statistics are calculated as a function at forecast lead times 30, 60, 90, 120 minutes. Mean error:

$$ME = \frac{1}{N}\sum_{i=1}^{N}(SIM_i - OBS_i)$$

Root mean square error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(SIM_i - OBS_i)^2}$$

SIM_i is the forecasted inflow and OBS_i is the observed inflow.

The KPI values are reported in three Microsoft Power-BI live-reports. A fourth report shows the rainfall predictions for the next 12-24-36 h.

Two reports present data related to rainfall forecasts, based on a numerical weather prediction model. One report shows the predicted rainfall for five areas over the catchment over the next 36 hours. This report only shows the results from the last few weeks. The other report shows how well the predictions fitted with the recorded rainfall. This report goes back to 1. July 2022, with a few data gaps. The two other reports show the statistical parameters for the flow predictions compared with the measurements and the actual "hit-rate" in predicting the flow increases. Both reports include data from June 2021 to date.

For the in-depth analysis, it would have been relevant and useful to have additional reports providing an overview of the timeline marking when the different forecasts have been in operation. Another useful aspect we have identified and don't have considered beforehand, is that it could have provided a better performance overview if the KPI's somehow related to events. The current KPI numbers are calculated for the entire timeseries, i.e., dry weather, small rain and heavy rain. As the objective of the ML demonstration is to test the capabilities in predicting high inflows, the current calculation of the KPI for all data, somehow

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contaminates the KPI data. This conclusion is reached too late in the project to revise the principles but will be considered changed for the continued use.

Result Inflow forecast**:**

The data period covers 20. June 2021 until 20. October 2022, 16 months. The Figure 27 shows the full KPI report for the 16 months. The three blocks show statistics for the four different forecast periods, 30-60-90-120 minutes. The three blocks display results for following three different forecasts:

1. MIKE+ BASE – hydrodynamic model, base scenario
2. ML – Machine Learning model
3. STAR – existing forecast based on a simple reservoir model

A general note on the numbers is that although they overall cover the same period, the actual forecast methods have been active with different percentages/coverage in the total reported period from June 2021 to October 2022.

The STAR forecast has been in operation for several years before DWC project, and there has been few interruptions during the project period, so the coverage is close to 100%.

Figure 26 gives an overview of the "up-time" for the different forecast method, and the alternative hydraulic control scenario, ICDAM2.

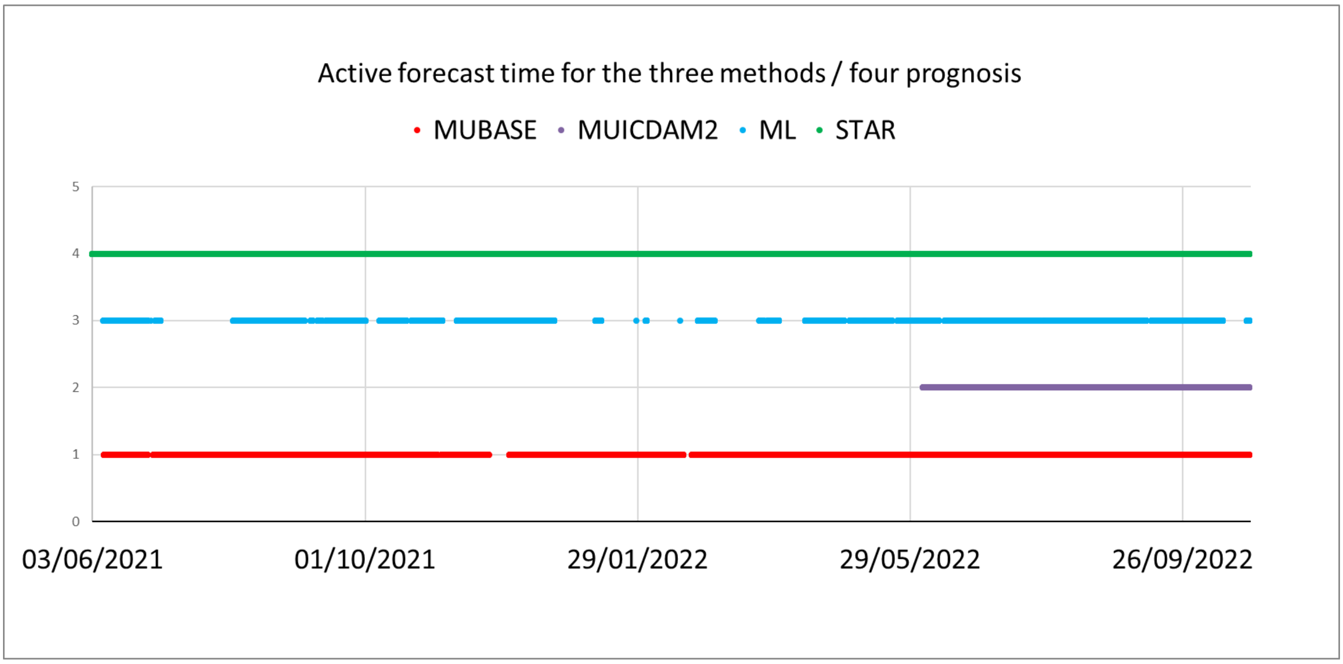

Figure 26: "Up-time" for the three different forecast methods, and the ICDAM2 alternative control strategy

The Hydrodynamic model (MIKE+ BASE) has been in operation in around 85% of the time during the DWC project. The ML has a relatively shorter, accumulated time in operation. Several challenges and constraints have caused interrupted operations, including fall-out of

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radar data, forced software updates of MLOps, license issues, etc. These challenges have caused DHI to plan to re-engineer the implementation into a more robust IT environment, a

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work that is planned to be executed before the end of 2022. This will allow a continued demonstration period until summer 2023.

The KPI report illustrated below in Figure 27, shows the stats for KPI inflow forecast report, for the period 20/6/2021 to 20/10/2022, shown as numeric table as well as histograms.

Styring	Average of ME	Average of MEneg	Average of MEpos	Average of RMSE	Count of MEneg	Count of MEpos	Count of RMSE
MIKE+ BASE 030	-219	-1648	931	1108	4503	5318	11293
MIKE+ BASE 060	-188	-1488	921	1114	4638	5184	11294
MIKE+ BASE 090	-177	-1597	952	1096	4451	5368	11291
MIKE+ BASE 120	-135	-1479	952	1120	4473	5346	11291
ML 030	317	-682	817	771	2095	5117	8809
ML 060	316	-702	808	776	2080	5257	8809
ML 090	311	-746	817	797	2083	5254	8809
ML 120	321	-787	821	807	1991	5346	8809
STAR 030	141	-1081	853	1033	3612	6497	11617
STAR 060	75	-1413	894	1121	3554	6588	11614
STAR 090	42	-1558	913	1173	3549	6594	11615
STAR 120	22	-1641	918	1202	3536	6604	11612

Figure 27: Stats for KPI inflow forecast report, for the period 20/6/2021 to 20/10/2022, shown as table and histogram.

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Table 17 includes the following statistical parameters for a user specified period, from a comparison between forecasted and measured individual timeseries points, where positive values indicate that the forecasted value is above the subsequently measures value with the same timestamp: 1) Mean error, 2) Average of mean error negative, 3) Average of mean positive, 4) Average of Root Mean Square error, 5) Count of "MEnegative", 6) Count of "MEpositive" and 7) Count of RMSE. The right side – the columns – shows the RMSE (up, positive values) and Average of "MEnegative" (down, negative values).

Table 17: Root mean square error values [l/s] for the hydrodynamic model MIKE+, the ML model and STAR for forecast lead times between 30 and 120 min.

Time (min)/Model	MIKE+ BASE	ML	STAR
30	1108	771	1033
60	1114	776	1121
90	1096	797	1173
120	1120	807	1202

The Root Mean Square error in Table 17 summarizes the "accuracy" of the forecasts compared to the subsequent measurements. While the results for MIKE+ BASE and STAR are on the same level, they have both a significantly higher RMSE, around 50% than the Machine Learning.

This indicates that the machine learning in general has a better prediction score. Unfortunately, the active time for the ML is somewhat lower than for the other methods.

Table 18 compares the RMSE for the two methods ML and STAR (existing forecast) for the 4 different forecast horizons. As it can be seen, the relative improvement is between 25 and 33 %, which is lower than the defined target KPI 1 of 35 % - 42 %.

Table 18: Root mean square error values [l/s] for the ML model and STAR for forecast lead times between 30 and 120 min. KPI values for RMSE. KPI 1.

Time (min)/Model	ML	STAR	Accuracy increase
30	771	1033	25%
60	776	1121	31%
90	797	1173	32%
120	807	1202	33%

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8.3.2. KPI 2: Accuracy of forecast time for wet and dry weather – up to 36 h

The aim of accurate dry weather forecasts is to allow BIOFOS and the catchment utilities to empty the storage basins more dynamically and geographically flexible, all depending on where and when it rains.

The forecast predictions and the comparison between forecasts and measurements are performed for five locations within the catchment, see Figure 28. For each location, a new forecast is produced on an hourly basis. The forecast is presented as a table, where minimum and maximum rain depths are listed for 12h, 24h and 36h ahead. The table is updated 4 times per 24h period. The forecast overview is shown in Figure 29.

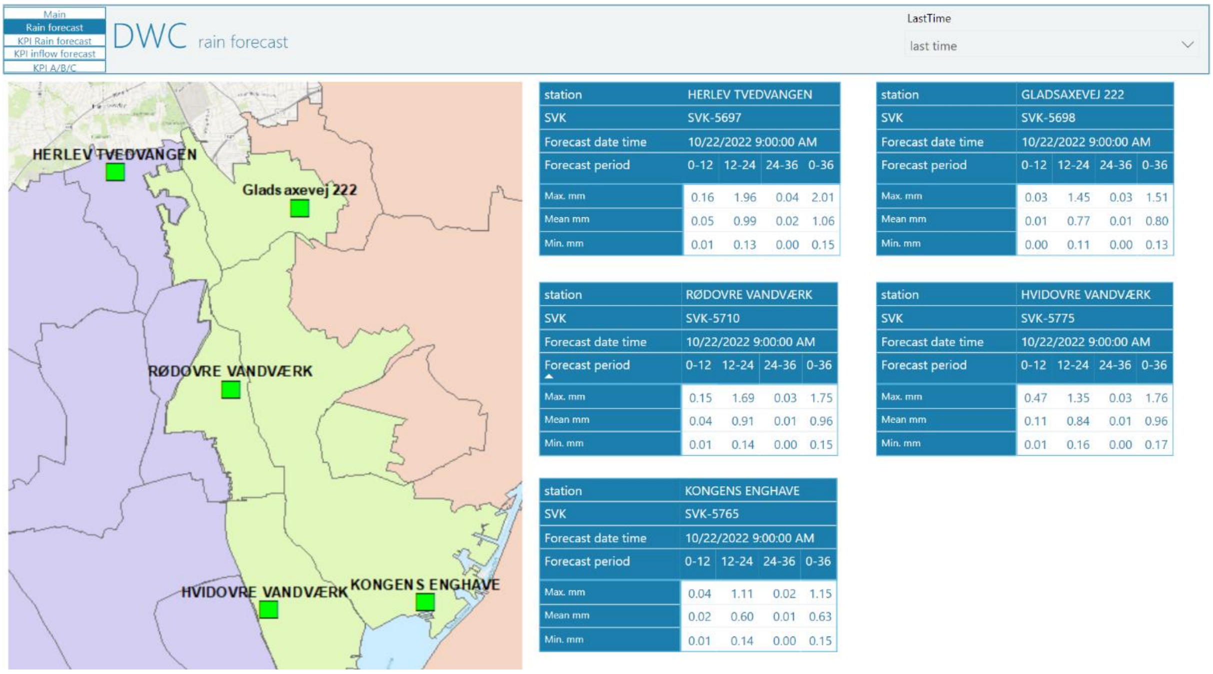

Figure 28: Rainfall depth forecasts for 5 locations within the treatment plant catchment. Forecast up to 36 h ahead. Each green square represents a rainfall measurement station.

__Result rainfall forecast:__

A separate report, shows the accuracy of the predictions, when compared with rain gauge data. For each of the five rain gauges, the 12-hour measured rain is matched (green columns) with the 12-hour NWP predictions (blue columns) at the same location. The user can zoom into different periods. The figure shows the period from 14. September to 12. October 2022.

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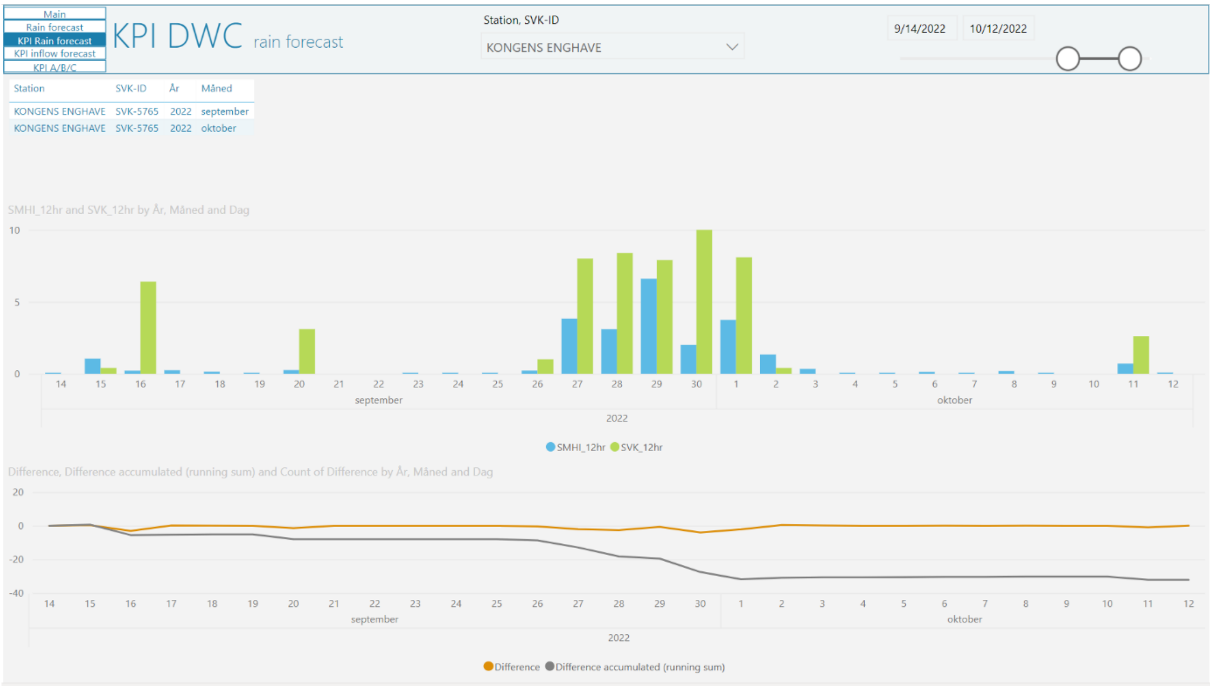

Figure 29: Comparison of 12 h predicted and measured rain depth, per day, including accumulated "error". Station name: Kongens Enghave.

For the specified period, the actual measurement over time shows higher values than the NWP predicted values. The same pattern or bias are seen as a general trend independent of the period. This issue has not been further investigated.

Accuracy of forecast time for dry weather – 36 h

For four of the five rainfall forecast locations, rain data were also available from rain gauges. The forecast accuracies show very similar results for all four stations, where the accuracy is in the range between 68% (36 h) and 88% (12 h).

Table 19: Comparison between forecasted and measured rain. Count is the number of hours in the different categories.

	0-12h	0-24h	0-36h
Rain is forecasted	1861	2314	2518
Dry period is forecasted	5258	4790	4577
Correct dry forecast	4624	3678	3096
Wrong dry forecast	634	1112	1481
KPI as % of correct dry forecast	88%	77%	68%

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8.3.3. KPI 3: Reduction of wrong automatic switching between dry and wet weather operation at the WWTP

The KPI evaluates whether the new inflow forecast models are better than the existing operational inflow forecast model, thereby reducing the wrong switches between dry and wet weather operation at the plant. This is done by comparing current linear reservoir model (STAR) with the ML and MIKE+ BASE – hydrodynamic model, regarding wrong starts, missing starts and correct starts.

Calculations are currently set up with lead times 30, 60, 90 and 120 minutes. Does an inflow forecast value exceed the threshold of 6,400 m³/h at the plant, once the switching from dry to wet weather operation (ATS- Aeration Tank Settling) is initiated. Other activation protocols include measured inflow at "Dæmningen", a location upstream the WWTP in the catchment, exceeding 3,000 m³/h once. The ATS is de-activated and dry weather operation resumed when the measured inflow at the plant is ≤ 4,000 m³/h.

The measured inflow to the WWTP in the period June 2021 to mid-October 2022 is shown in .

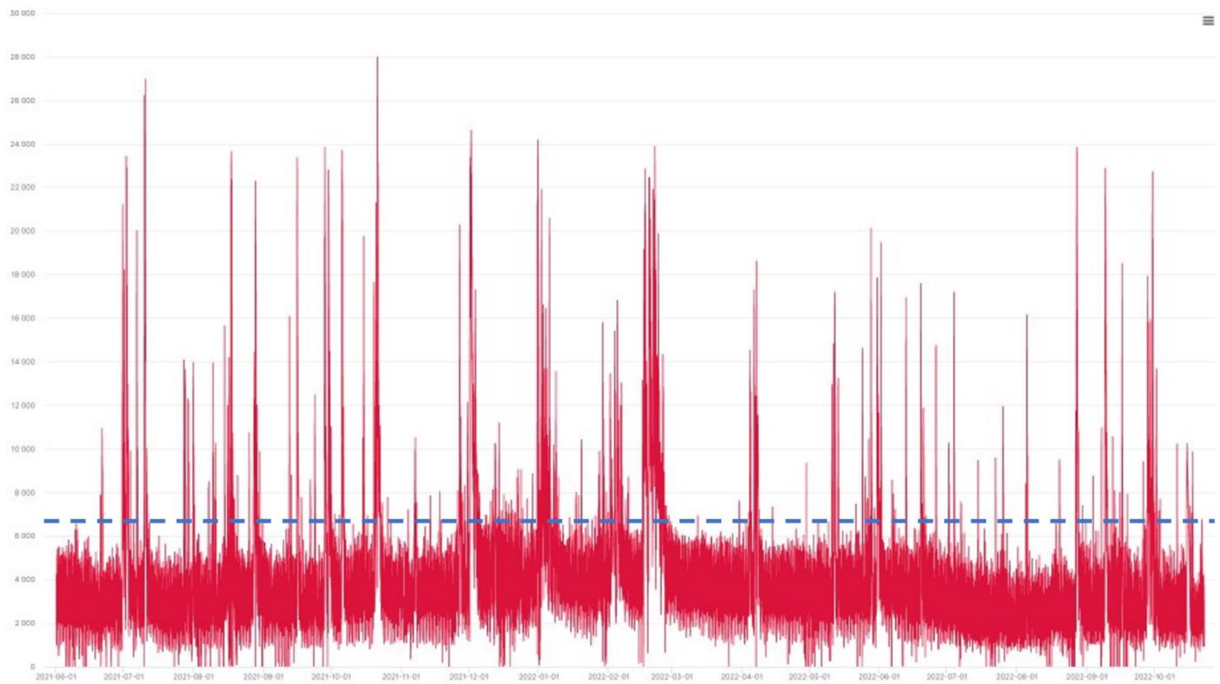

Figure 30: Measured inflow to Damhusåens treatment plant from June 2021 to October 2022. The horizontal line indicates the threshold value for switching between dry and wet weather control, 6400 m3/h .

Within the period, there has been around 300 starts of wet weather control, some of which have lasted for several days.

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Definition of correct start (A) Correct warning:

- Both the flow forecast activated wet weather operations (ATS-control) and measured inflow exceed the threshold of 6,400 m^3/h during 2 times forecast lead times from the start of a forecast. If the actual measured flow exceedance occurs sooner than the forecasted exceedance, it is also considered a correct start.

Definition of wrong start (B) – False warning, KPI 2:

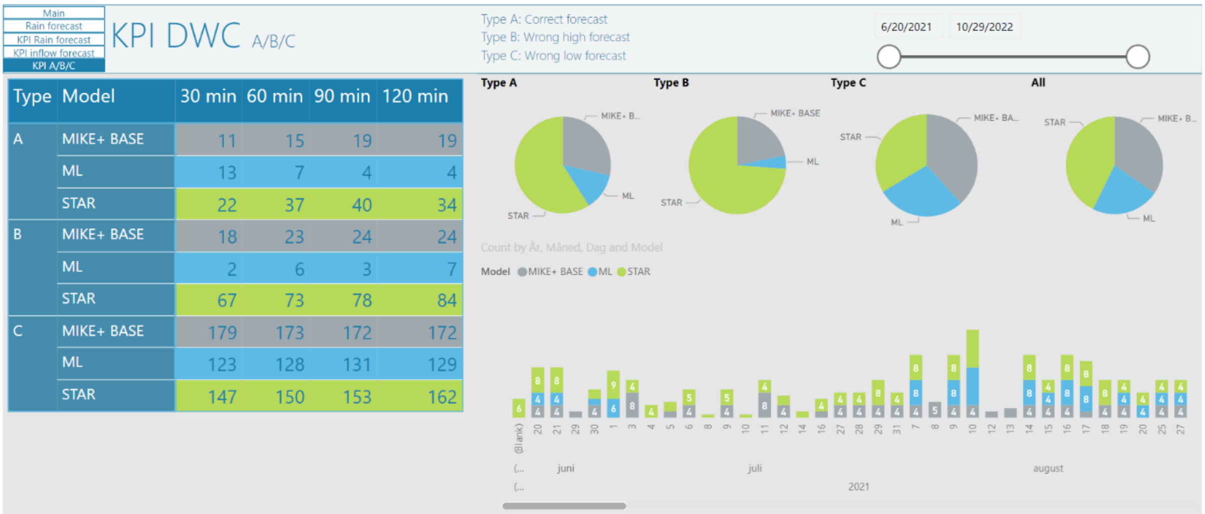
- The forecasted flow exceeds the threshold value of 6,400 m^3/h (and triggers the change from dry weather to wet weather control) but the measured inflow at the plant did not exceed the threshold within a period of two times the forecast lead time from the start of a forecast.

Definition of missing start (C) – Missed warning:

- Measured inflow activated the wet weather control: The inflow exceeds 6,400 m^3/h without wet weather operation (ATS-control) active or the flow at "Dæmningen" exceeded 3,000 m^3/h, and neither of the prediction methods forecasted flows exceeding the threshold value.

shows the KPI report for the A/B/C values. It shows the number of occurrences for the different forecast lengths as well as relative accumulated A/B/C scores for the three different forecast methods:

- MIKE+ model, also called HIFI model and hydrodynamic model
- Machine learning – ML
- Linear reservoir model, existing forecast - STAR



Type	Model	30 min	60 min	90 min	120 min
A	MIKE+ BASE	11	15	19	19
	ML	13	7	4	4
	STAR	22	37	40	34
B	MIKE+ BASE	18	23	24	24
	ML	2	6	3	7
	STAR	67	73	78	84
C	MIKE+ BASE	179	173	172	172
	ML	123	128	131	129
	STAR	147	150	153	162

Figure 31: The ABC KPI report, summing up numbers for correct warning, false warning and missing warning. The numbers are not directly comparable, as the prediction methods have not been in operation in the same accumulated time.

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The sum of correct and false alarms (A+C) is at the same level for each method for the varying forecast lengths. The numbers for ML are significantly lower than for the hydrodynamic model and STAR, probably explained by the shorter time ML has been operational.

Table 20: Sum of true and false alarms for the different forecast lengths.

	30 min	**60 min**	**90 min**	**120 min**
MIKE+ BASE	190	188	191	191
ML	136	135	135	133
STAR	169	187	193	196

When looking into the reliability of high flow forecasts (exceeding the 6400 m3/h), there is a significant difference between the different forecast principles.

The relative score for the three methods can be calculated:

- MIKE+ BASE (11+15+19+19) / ((11+15+19+19) + (18+23+24+24)) = 41%,
- ML = 61%
- STAR = 31%

or in words:

For MIKE+ BASE the prediction is correct in 41% of the high flow forecasts, for ML it is 61% and for STAR it is 31%.

When it comes to the number of missed high flow predictions (Type C), the ML has a slightly lower number, which may relate to the relatively shorter up-time.

KPI 3: Reduction of wrong automatic switching between dry and wet weather operation at the WWTP. The total number of false starts for the existing STAR forecast and the ML are (Type B): 67+73+78+84=302 and 2+6+3+7=18. Although the false start count for STAR covers a longer up-time period than for ML, there is a significant improvement when it comes to reducing the number of false starts by using the ML. The ML seems to reduce the false start count with around 90% or more.

Result summary, KPI #1, KPI #2, KPI #3:

KPI 1: Inflow forecast

The inflow predictions of the ML forecasts, expressed as RMSE, is around 30% better than the existing STAR and the hydrodynamic model results. With the challenges related to gaps in

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continuous data supply for the ML routine, it is expected that the ML can perform even better with a stable and continuous supply of real time data from the catchment.

KPI 2: Dry weather flow forecast

The prediction of the dry weather for 12-24-36 h ahead, has an accuracy score of around 75-80%.

KPI 3: Reduction of wrong switches from dry- to wet-weather operation of the treatment plant

The ML routine provides a significant improvement in the number of wrong switches, in the order of a 90% reduction.

8.3.4. Other benefits

There are several benefits of the modelling methodology. One benefit is a higher degree of automation in model building, rather than the physics-based approach which requires several intermediate parametrized models. For instance, in the case of using weather radar observations, the traditional model chain comprises the Marshall-Palmer relation for translating radar reflectivity to rain intensity, bias correction of radar rainfall using rain gauge data, rainfall-runoff modelling, and hydrodynamic modelling of the sewer system for flow prediction. The ML model uses weather radar data to predict a rain intensity category, which is used directly to predict flows without additional modelling steps. Another advantage is the speed at which forecasts can be made, which is on the order of seconds. Additionally, it is easy to train models for even longer lead times if desired.

8.4. Return on experience

Working with inflow prediction, we gathered experience from machine learning experiments as well as with setting up a running system. Our findings are described in the following.

Data availability: Retrieving historical data from offline databases at utilities was a huge effort. Likewise, it took a long time to set up data flow to maintain an updated database in the cloud, necessary for retraining of the machine learning models and to make predictions as requested through the web service we set up. Sometimes data is not available from the utilities providing data, in which case predictions cannot be made. As a remedy, we have developed five different ML models, covering the combination of interrupted data source. All five models have been trained with historical data. If a data source is missing, the ML model that corresponds to the available input data is used.

Reproducibility and result comparisons for ML models: We use an MLOps platform (software development environment) hosted in the cloud (we use Azure), which has turned out to be very useful in tuning and retraining machine learning models, versioning models, keeping track of models and training and evaluation results, and for model deployment. But the MLOps/Azure environment is at the same time relatively costly, and with frequent software updates, it requires significant maintenance. We have decided to migrate the trained ML routine to a different IT-environment, which offers slightly slower performance but a more

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reliable, stable and less expensive framework. This work is scheduled for December 2022, and the project partners will extend the testing period for another six months in 2023.

Another conclusion/recommendation is related to the hydrodynamic model. The model has a hotstart feature, that forces it to start from the previous simulation. This feature can be further enhanced, and it will especially during wet weather provide significant better results. Another possible improvement is to introduce the so-called data assimilation, there the hydraulic model is “forced” to use the latest measured flows as initial conditions.

Practical implications and considerations for the future: BIOFOS consider ML as an alternative method to the existing STAR- linear reservoir model for predicting the inflow to the WWTP and usage in operations. ML shows promising forecasting results, and the potential to implement it at other locations (WWTP or CSO) and in a dynamic integrated control in the catchment, is high. BIOFOS will therefore allocate time in promoting the results within BIOFOS operations and the Integrated Wastewater Management Group for Greater Copenhagen with the aim to establish further innovation as well as real testing in operations.

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9. DS12: Interoperable decision support system and real-time control algorithms for stormwater management

9.1. Digital solution

DS12 "Interoperable Decision Support System (DSS) and real-time control algorithms for stormwater management" aims to support the sewer system- and WWTP operators to choose the best control strategy to minimize pollutant loads based on a comparison of inflow forecasts (DS11) and control strategies. The aim of the demonstration is also to build awareness and confidence across operators to trust on a DSS based on model results.

The Decision Support System (DSS) addresses two different control strategies in the network as well as executing the ML model matching the input data availability. The aim to look into two control strategies is to evaluate the potential to optimize the utilization of relevant retention capacities in the system, thereby minimizing bypass at the WWTP and saving CAPEX investment costs for a retention basin at the WWTP to obtain the same benefit.

Two different model types are used in the project to obtain results and evaluate benefits. The ML models described in the previous section and the HIFI model, also called hydrodynamic model and MIKE+. The HIFI model is a calibrated hydrodynamic model, describing the detailed flows and levels throughout the pipe network. The HIFI model is configured to execute two different pre-defined control strategies. One being the default control setting (MIKE+ BASE) the other an alternative control strategy (MIKE+ ICDAM2), which aims to optimize the management of in-sewer retention capacity and emptying of retention basins. The output of the HIFI model and the two control scenarios are very similar: inflow forecasts to the treatment plant, but only looking 2 hours ahead as compared to the 3-hour ahead forecasts from the ML models, due to performance restraints.

DS12 is a software component that integrates DS11 and DS13. DS12 enables simulations of different scenarios, compiles and manages results and KPIs to be visualized in DS13. User interaction with the DSS takes place in the web interface (DS13).

9.2. Demo description

The DSS has been set up and tested for the Damhusåen study site in Copenhagen. The demonstration includes a comparison of inflow forecasts and control strategies. Simulated real-time tests are carried out using radar data to produce deterministic inflow forecasts for screening and evaluating real-time control algorithms for WWTP operations and management of retention capacity in the catchment.

Control scenarios:

The utility HOFOR, an associated partner in the project, has recently constructed two big storage tunnels along a river called Damhusåen. To further enhance the utilization of one of the tunnels (29,000 m^3) and thereby reducing bypass at the WWTP, an alternative control strategy is set up in the HIFI-model called MIKE+ ICDAM2. The new strategy implies the insertion of a sluice gate between the existing gravity pipes and the tunnel. During rain events the gate will make it possible to force water into the tunnel earlier than it is possible today. The controls between the inflow to the WWTP and the gate are set in such a way, that water is forced into the tunnel at inflow rates of above 8,000 m^3/hour at the plant as long as the level in the tunnel does not exceed a certain set-point, assuring that the alternative control strategy does not conflict with other strategies in the catchment and/ or provoking a CSO to the local creek. The maximum biological capacity at the WWTP is 10,000 m^3/hour, which means that all inflow exceeding that threshold bypasses the biological treatment at the WWTP and is only treated mechanically.

Today water enters the tunnel through internal overflow structures from the gravity pipes when the capacity in the gravitational pipes is fully used. The benefit of redirecting the water earlier is, that the inflow to the WWTP via the gravitational pipes can be reduced. Even though it will be necessary to run long term simulation to reveal the real potential of the suggested control scenario, the demonstration of saved bypass volumes and reduced nutrition loads, coupled with the results on long-time weather forecast will bring us a considerable step further in the process of optimizing real-time control of existing infrastructure.

9.3. Assessment of the digital solution

The benefits of the solution have been assessed via three defined key performance indicators (KPI). The two HIFI-models are running online simultaneously since the 01.07.2022. Data included in the assessment and discussion includes the period 01.07.2022- 29.10.2022.

Because of the relatively short period of evaluation and the initial intention to calculate annual reductions of by- pass volume, nitrogen emissions and CAPEX cost- savings, BIOFOS has decided to also include calculations of the KPIs for a practical, real-life example. BIOFOS and HOFOR (utility) have implemented an integrated control strategy (ICDAM1) in June 2020, where the effects and benefits are monitored and evaluated continuously.

This means that this section will include KPI calculations for:

- Inflow forecast results (30min) of the two HIFI-models, MIKE+ BASE and MIKE+ ICDAM2 in the period 01.07.2022- 29.10.2022.
- Measured data of the implemented control strategy between BIOFOS and HOFOR- ICDAM1.

The results are summarised in Table 21. Details on considered input data as well as calculations are given in the subsections below.

Table 21: Overview table of KPI assessment

KPI	Short description	Quantification
Reduction of by-pass volume [m^3]	The aim of the KPI is to calculate the absolute reduction of the annual volume of only mechanically treated combined sewage (bypass) at the WWTP discharging into marine	Bypass reduction with ICDAM2 compared to the base scenario = 25.000 m^3.

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KPI	Short description	Quantification
	waters by comparing the alternative control strategy with a base scenario. Bypass reduction regarding ICDAM2 and the current practice is calculated as total and per month for the period 01.07.2022- 29.10.2022. Annual reductions are calculated for the already implemented control strategy ICDAM1.	Annual bypass reduction with ICDAM1 = 820.000m^3 equal to a 25% saving.
Reduction of nitrogen (N) emissions [tons], [%]	The aim of the KPI is to calculate the reduction of nitrogen emissions to the recipients with the alternative control scenario in the catchment and the advanced integrated control between WWTP and sewer network operator. This includes CSO volumes along the river and connected to the storage tunnel.	Reduction in nitrogen (N) with ICDAM2 is 0,4 tons or 7% compared to the base scenario. In 2021 the reduction of nitrogen (N) emissions achieved by ICDAM1 were 13 tons. This corresponds to a saving of 19% compared to no control strategy.
CAPEX reduction for constructions to reduce bypass	The idea with the KPI is to calculate the investment cost for constructing storage volume at the WWTP equivalent to the obtained effect with the new control scenario established in DWC, based on model results. Since simulation do not really mimic reality, this KPI is illustrated theoretically and calculated for ICDAM1.	CAPEX savings with ICDAM1 are approx. 75mio.EUR.

9.3.1. KPI 1: Reduction of by-pass volume [m^3]

The KPI calculates the absolute reduction of the volume of only mechanically treated combined sewage (bypass) at the WWTP discharging into marine waters by comparing the alternative control strategy with a base scenario (current practice). By-pass occurs when the inflow exceeds 10,000 m^3/ hour.

1. *Reduction of by-pass volume [m^3] based on forecast data (30 min) for MIKE+ Base and MIKE+ICDAM2 during the period 01.07.2022- 29.10.2022*

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During the period 01.07.2022- 29.10.2022 the simulated bypass volume by MIKE+Base and MIKE+ICDAM2 was 276,000 m^3 and 251,000 m^3 respectively. This means that the alternative scenario saved the environment for a total of 25.000 $m^3$of bypass.

However, is the simulated inflow to the WWTP considerable overestimated and measured bypass volume at the WWTP is only 172,000 m^3 during the same period. It must unfortunately also be stated that, besides magnitudes of bypass volume, the simulated events do not necessarily lie at the same point in time.

There are several possible explanations for that: one is that the forecast is based on radar data and therefor estimated rainfall, which often can be very different to the finally measured rainfall. Another explanation is that the model's catchment/ runoff description as well as the control strategy itself are insufficiently described and/ or with errors.

Table 22 shows the total calculated bypass flow per month for MIKE+ Base, MIKE+ ICDAM2 and measured bypass at the WWTP.

Table 22. Calculated bypass flow per month for MIKE+ Base, MIKE+ ICDAM2 and measured bypass at the WWTP.

	Calculated bypass volume [m^3]		
	MIKE+Base	MIKE+ICDAM2	Measured
July	80,260	69,802	13,282
August	179,569	144,455	29,918
September	7,403	14,589	121,285
October	8,435	21,819	8,503
TOTAL	**275,668**	**250,665**	**172,998**

As can be seen in the table, differences between simulated and measured bypass are significant and the results are therefore only of limited use regarding benefit evaluation. Regarding the opposite effect for ICDAM2 in September and October, a closer look into the data shows that the model simulates unrealistic single datapoints, which are the reason for the opposite results in September and October between the scenarios.

2. *Reduction of annual bypass demonstrated with the integrated control strategy ICADM1*

BIOFOS still believes that the alternative control scenario, when simulated correctly, would reduce the volume of bypass at the WWTP. To illustrate the huge effect which can be obtained by optimizing the system, annual bypass savings obtained with another integrated control strategy, implemented between catchment and WWTP (BIOFOS and HOFOR) is presented

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here. Effects and benefits are monitored and evaluated constantly via measurement data and calculations.

In 2021 ICDAM1 resulted in a reduction of 820.000 m^3 in bypass, which represents a saving of 25% of the total bypass emitted. BIOFOS registered a total bypass volume of ca. 2,358,000 m^3, while it would have been 3,178,000 m^3 without the integrated control strategy ICDAM1.

9.3.2. KPI 2: Reduction of nitrogen (N) emission

The aim of the KPI is to calculate the reduction of nitrogen emissions to the recipients with the alternative control scenario in the catchment and AIC (Advanced Integrated Control) between WWTP and utility. Nitrogen is the primary concern, and hence chosen as KPI, as BIOFOS has to reduce nitrogen emissions with 200 tons/year to comply with the EU-Water Framework Directive. BIOFOS complies with phosphorous emissions. Therefor simulation results of both saved bypass in the storage basin and volumes at CSO are included in the KPI. To be able to compare the effect of the alternative control strategy, the same results are stored in the baseline simulations running simultaneously.

A part of the KPI is the water balance accounting for the difference in bypass volume due to reduced inflow to the plant during a rain event. Reduction of nitrogen emissions are calculated as percent reduction and totals in tons.

$$KPI\ 2\ [\%] = \frac{(N_{old} - N_{new})}{N_{old}}\ x\ 100$$

Where *N* stands for nitrogen, the subscript *old* refers to the initial control strategy, while *new* refers to the integrated control strategy, where the usage of basin volume is optimized regarding the biological treatment capacity at the WWTP without compromising CSO.

Using the results from the section above, the difference in total *N* between the two scenarios within the 4 months is 7% or 0,4 tons. However, since the model and input set-up have to be revised, this result is not representative.

Regarding the reduction of nitrogen emissions with ICDAM1 in 2021, BIOFOS saved 19% *N* emissions, or 13 tons *N* compared to no control strategy. Regarding the mentioned requirement of reducing nitrogen emissions with 200 tons N/ year, ca. 7% is delivered by this integrated control strategy. In the next section this volume is used in the CAPEX saving calculation.

9.3.3. KPI 3: CAPEX reduction for constructions to reduce bypass

The idea of evaluating whether the alternative control strategy is cost-effective by calculating the investment cost for constructing storage volume at the WWTP equivalent to the obtained effect with the alternative control scenario is illustrated by ICDAM1, since simulation results are not reflecting reality good enough to estimate cost-savings.

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Figure 32**Fehler! Verweisquelle konnte nicht gefunden werden.** below shows the relationship between storage volume and bypass reduction. Input data for the calculations was measured inflow to the WWTP Damhusåen during 2020 and a biological treatment capacity of 10,000 m^3/time. The year 2020 had an annual precipitation of 613mm, which represents a normal precipitation year.

To obtain a reduction of bypass volume of 820.000 m^3 per year and thereby achieve the same environmental benefit as with the implemented control strategy ICDAM1, a storage volume of 30.000 m^3 is necessary.

With an actual price of approx. 2,500 EUR per m^3 storage volume, BIOFOS would need to invest around 75mio. EUR to obtain the same effect.

See Figure 33 or the relationship between storage volume, bypass reduction and costs.

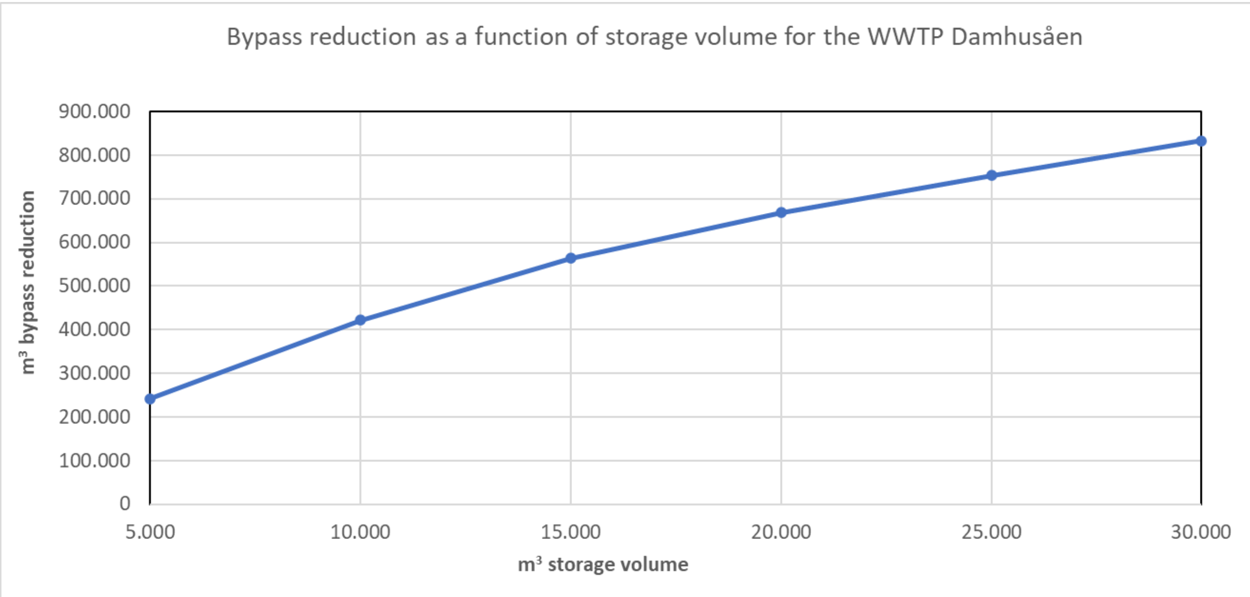

Figure 32: Relationship between bypass reduction and basin volume. For example, to achieve a reduction of 830,000 m^3 in bypass per year, you would need a storage basin volume at the WWTP Damhusåen of 30,000 m^3.

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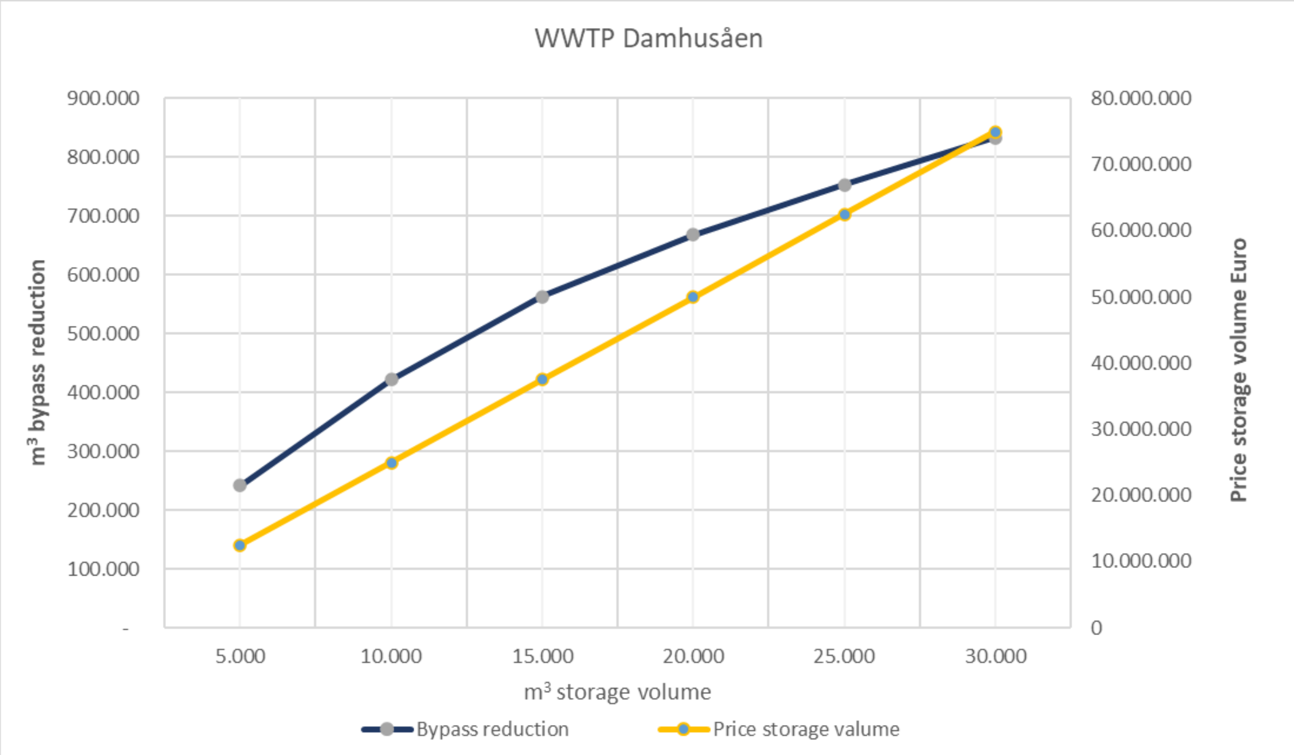

Figure 33: Relationship between bypass reduction, necessary storage volume and storage volume costs for the WWTP Damhusåen.

9.4. Return on experience

Performance quality of the forecast models had to be assessed and ensured at multiple stages i.e. before as well as after operationalization. For example, prior to operationalization, multiple 'offline' checks on the HIFI model had to be performed using historical events to make sure it can realistically simulate inflows to the wastewater treatment plant during dry- as well as wet-weather days. Then, forecast performance after operationalization (i.e., online) was also necessary as the system has other components in addition to the HIFI model, such as input pre-processing routines used before each forecast run, or other external components, such as radar rainfall forecasts that are used as input to the model. If the operational forecast of inflow to the wastewater treatment plant is deemed poor compared to measurements, several aspects of the operational system and not just the HIFI model itself, need to be revisited and adjusted. Aside from possible limitations of the HIFI model in, e.g., simulating particular types of wet-weather events, the problem could also be due to bugs in input pre-processing scripts, or even inherent poor quality of the rainfall radar forecasts used as input to the operational model, and the possibilities for making corrections / adjustments vary among these components.

Moreover, evaluation of the operational system forecasts depends on the occurrence of wet-weather events over which they could be performed. Wastewater inflows during rain events

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are of main interest in the project, and thus, more complete checks on operational model performance could only be made upon availability of wet-weather rainfall input and inflow measurements during rainy periods.

Regarding development and implementation of control scenarios, we needed to consider not just technical viability of options (i.e., in the model setup), but also practical considerations, such as if these control options could be implemented in real life. For example, the HIFI model is built using software that allows addition of numerous options for storage or evacuation of water from the sewer system, e.g., via addition of new structures such as pumps or gates, or of control rules to existing controllable devices described in the model. However, the types and locations of control options introduced to the operational model first had to be deemed viable for actual implementation by the utility company. It was important to ensure that the control scenarios implemented in the operational system were practicable in real life, and this imposed additional limits to the options that could be implemented / tested in the operational system.

Practical implications and considerations for the future:

To be able to use the HIFI-models as decision support tool, some improvements are suggested. The model needs an updated re-calibration using the radar data as rain data source. The model has only been calibrated on basis of ground-based rain gauges. Another suggestion, that will enhance not least the forecast accuracy, is to implement a so-called Data Assimilation (DA) procedure. DA is a recognised method for improving model forecast results for most mathematical models. In short, the DA method forces the prediction to assume the current situation (now) as initial condition before looking into the future. Besides, more offline simulations and result analysis regarding alternative scenarios must be performed before Operations will be willing to use forecasted effects of changed controls.

A detailed model analyses is outside the scope of this project, but BIOFOS will address the model challenges together with the utilities since these models are used for planning control strategies and investments in the catchment.

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10. DS13: Web-platform for integrated sewer and wastewater treatment plant control

10.1. Digital solution

The solution DS13 ("Web-based prototype platform for decision support at city scale") is a web platform, enabling implementation, execution, and visualization of DS11 and DS12. It provides a full overview of key data and processes to all involved share- and stakeholders[10]. Shareholder interest spans from simply overview to important information in the operator's decision-making process. Typical users for the platform will be planners, operators and middle management regarding KPI reporting. The platform includes both a GIS-like overview, with selected timeseries and an associated dashboard with key data, e.g., on rainfall predictions, associated uncertainties, hydraulic capacity of sewer pipes and storage tanks as well as the status of treatment processes. The solution fosters stakeholder engagement and rational decision making based on real-time data, accurate modelling, and scenario analyses. Important in this context is the goal, that all shareholders can download the processed data and integrate them in their own control strategies based on the same data sources. Figure 34 shows a screen capture of the entry web page, showing key sensors in the greater Copenhagen area. The web app offers further drill down, for visualization of monitored data, inflow predictions as illustrated in Figure 35 and Figure 36.

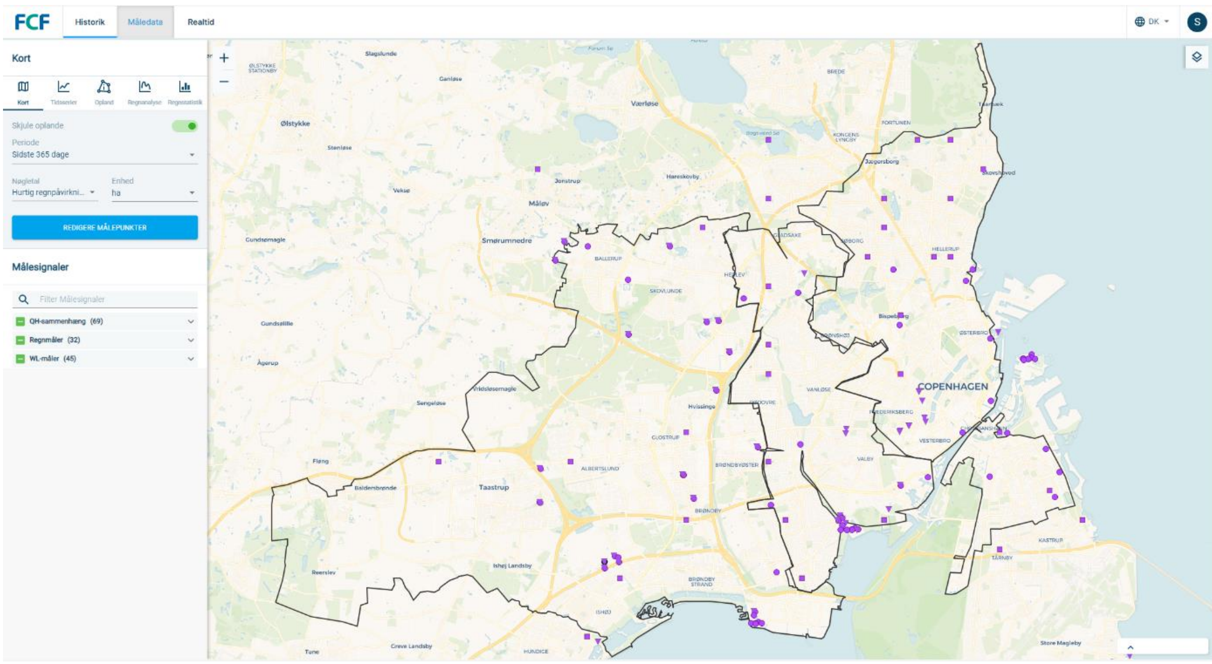

Figure 34: Screen capture of entry page for DS13. Map overview with dynamic links to all sensor stations

[10] Share- and stakeholders are BIOFOS and the 7 utilities in the catchment.

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10.2. Demo description

The solution DS13 provides detailed information on the actual monitored flows and levels in the catchment. The solution is embedded into a web-platform, Future City Flow (FCF), that has been tailored to manage and present flow data, FCF includes special features for real-time and long-term planning. FCF offers three different modules:

1. Time series storage. Repository for flows, levels, rainfall info. Data can be displayed, aggregated, exported and several other functions.
2. Real-time. Comparison of live scenarios including forecasts.
3. Planning. Long term rehab planning including financial optimization.

DS13 makes use of the two first modules of FCF, which in turn has been further enhanced to include the DWC requirements, like larger flexibility for showing different forecast methods

Separate views present timeseries up to the latest monitored values. Further, the tool allows for comparison of individual timeseries and exports. In the Real-time part of the DS13, the calculated inflow predictions are shown as 3-hours forecast. Four different forecasts can be displayed individually or jointly: machine learning forecast based on radar data and two HIFI forecasts, one for the base conditions and one for a predefined active control scheme for the alternative scenario (ICDAM2). Finally, the existing forecast system STAR is also included. The short-term flow forecasts are intended to be used by the operator to decide when to switch between dry and weather treatment control. The DS13 also includes a 36-h early warning of rainfall, as discussed and demonstrated in Section 10.3.2. Based on updated data from the Met-office's numerical weather predictions model, selected data are retrieved and consolidated into simple statistical views showing the risk of rain at different locations in the catchment. The long-term outlook is used to guide for emptying of larger retention basins or for planning of maintenance work (flushing pipes, replacing pumps and similar). Finally, the DS13 also includes presentations of the KPI's, some of which are calculated in real-time as temporal variables, see Section 10.3.3. The KPI reports are configured in Power-BI.

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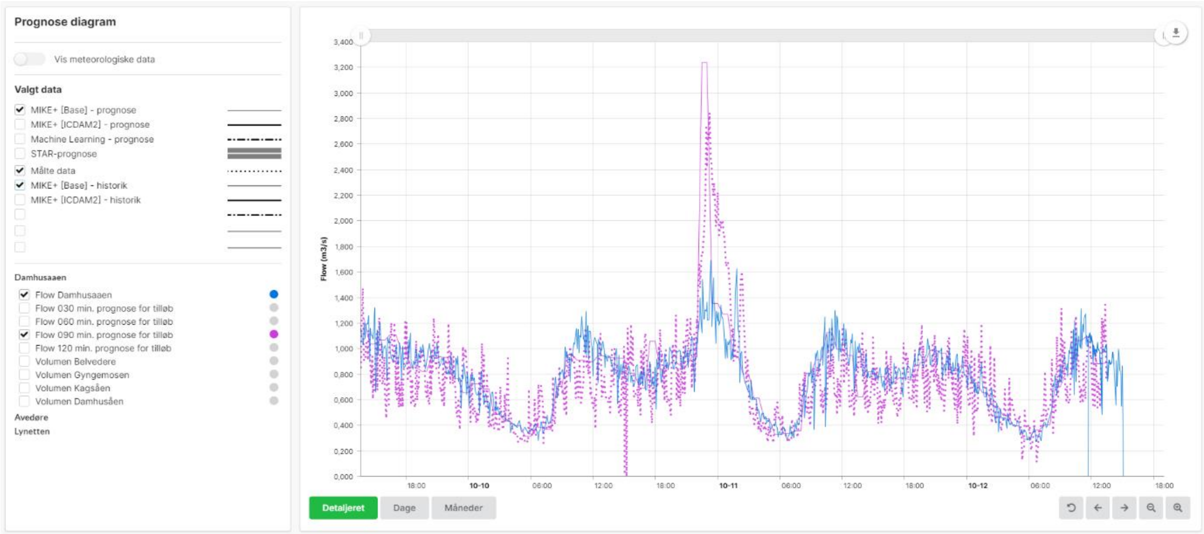

Figure 35: Screenshot of a simulated inflow forecast. The dotted purple line shows the measurements, and the thin full purple line is the 90 min forecast value from the hydrodynamic model

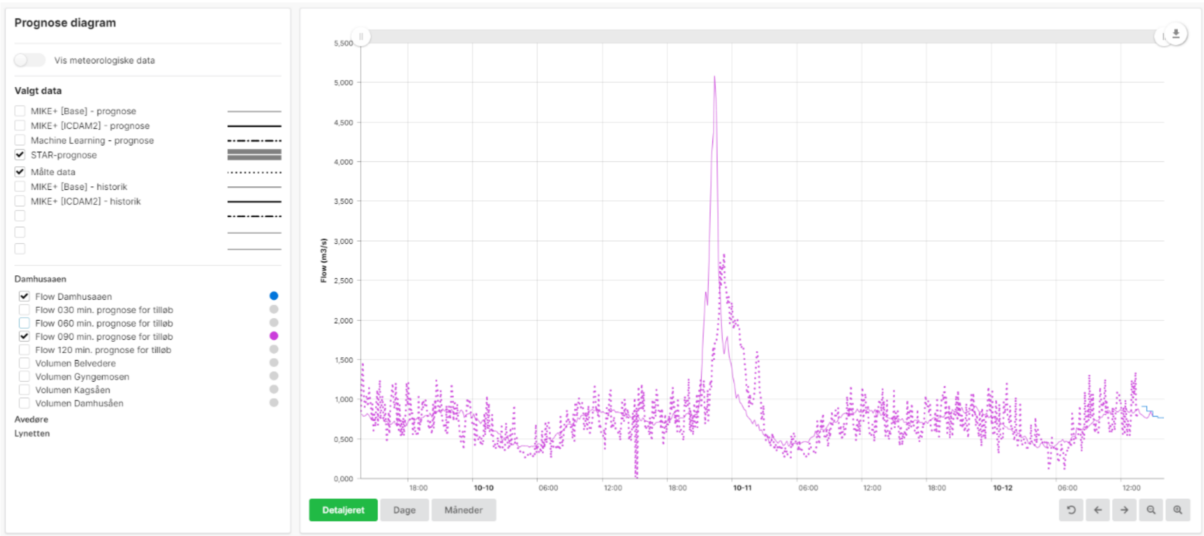

Figure 36: Screenshot of a simulated inflow forecast. The dotted purple line shows the measurements, and the thin full purple line is the 90 min forecast value from the star forecast.

Comparing the two figures above (Figure 35 and Figure 36), both the hydrodynamic model and the STAR model is able to forecast an increase in the flow in advance. The STAR model overestimates the flow peak, whereas the peak predicted by the hydrodynamic model fits almost perfectly. Unfortunately, the ML forecast was not operational at that moment.

Figure 37 shows an example of the ML forecast compared with the measurements. Note that the data is from a different period than the data in the previous figure.

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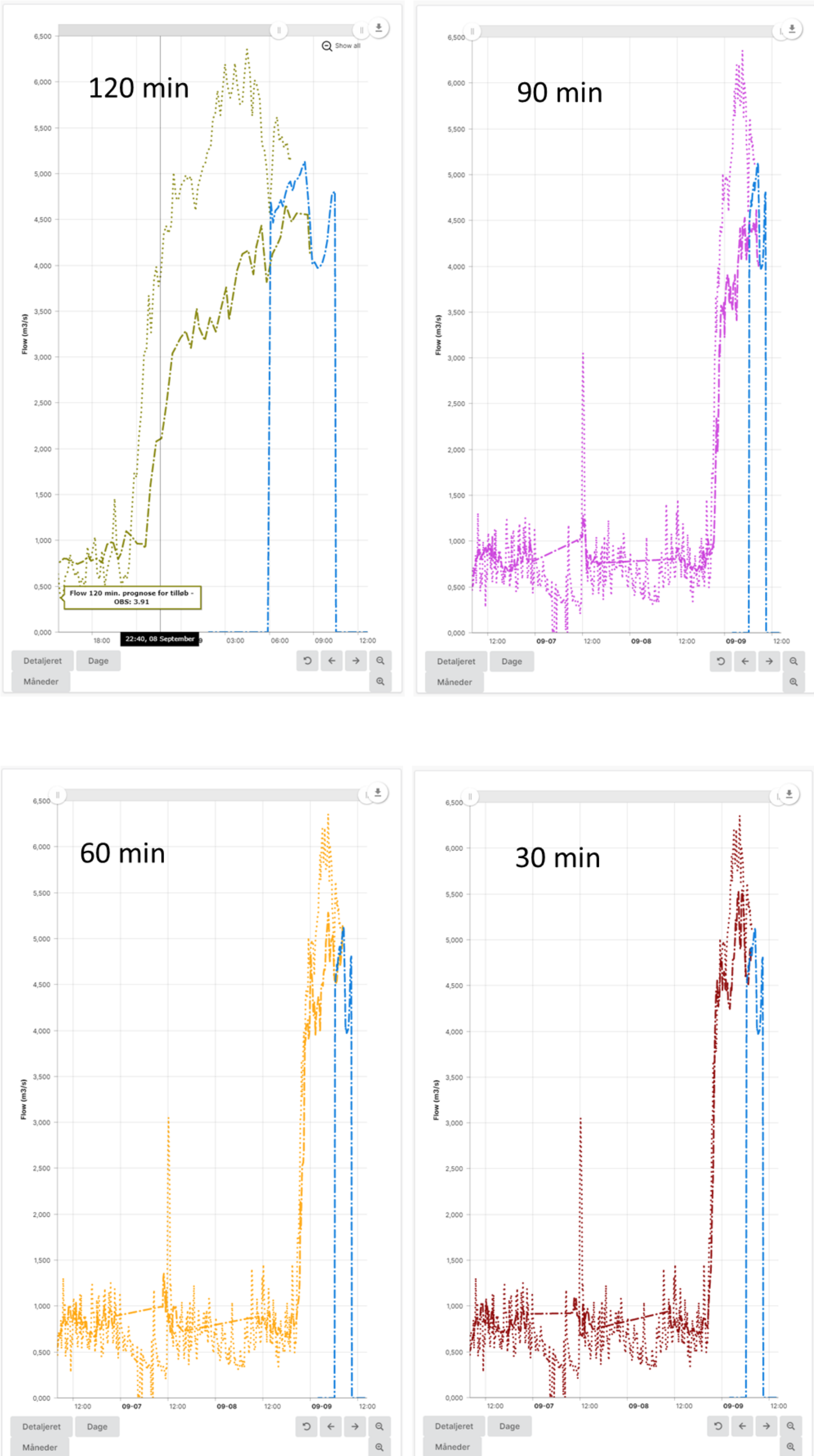

Figure 37: screen capture of a simulated inflow ml forecast. The four plots show how the forecast changes over time, from 120 min to 30 min. The blue curve is the latest actual forecast, the other curves show measured values (dotted line) and the forecast history for the different forecast periods.

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It can be clearly seen that the shorter the forecast period, the better the predictions.

10.3. Assessment of the digital solution

The benefits of the solution have been partly assessed via of the defined KPIs. The results are summarised in Table 23. Details on considered input data as well as calculations are given in the subsections below, where especially the section on return of experience gives a good overview over the benefits of the digital solution.

Table 23: Overview table of KPI assessment (to be completed)

KPI	Short description	Quantification
Increased usage, utility buy-in	There will be organized two workshops with relevant employees of the WWTP and staff of the stakeholder utilities in the catchment. Rate of workshop participation and reported willingness to use DS13 is evaluated.	80% of the 7 utilities are participating in workshops. – achieved. There are registered users from 80% of the utilities. – Not able to assess, since the platform first will be presented to the stakeholders in January 2023. At least 2 users will use the system on a daily basis, and at least 50% on a monthly basis. - Not able to assess, since the platform first will be presented to the stakeholders in January 2023.
Dashboards used by top management	The aim is that relevant (top-) managers (for example department chiefs) will use the created dashboards showing KPI indicators developed under DS11 and DS12.	A useability test will be conducted with members of management. - Expected in Q2/ Q3 2023. – After having used the system for some time.
Co- creation on functional design such as colors changing depending on remaining capacity in the system, icons etc.	Design workshops held with the Local Community of Practice (utilities) to enhance acceptance and up-take of the web-platform. This included discussions on icons, colors, possibilities of selection of time series, viewer for rain statistics etc.	1 workshop- Completed.

10.3.1. KPI 1: Increased usage, utility buy-in

To increase the usage and utility by-in, there will be organized two workshops with relevant employees of the WWTP and staff of the stakeholder utilities in the catchment. One workshop was held the 04.02.2021 with the assistance of “Icatalist” using an adapted version of a

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method known as the "pentagonal problem" as a basis for collecting feedback and expectations.

Key take-aways are, that the system must be easy to access and have an intuitive interface, show a high performance, and that all data is available for download. Of special use for the community is processed data such as rain statistics and visualized rain forecast, as well as that the system serves as data repository for data of the whole catchment. The group thinks that the system gives water utilities and planners the overview of actual and historical data over the catchment and thereby will facilitate a better use of assets across the catchment. One of the main benefits for BIOFOS' stakeholders is that the tool creates a general catchment awareness and can improve the communication between the utilities, to the authorities and the public. It has also been clear that a buy-in of the utilities to use the system highly depends on whether the system offers additional value to their own SCADA system.

11 of the 13 invited staff members were attending the workshop. One utility was not attending but input was collected via email by sending the questionnaire used during the workshop. The feedback of the utilities was implemented into FCF with special focus on increased performance and system usability.

The increased usage of the system with the following KPI quantification:

- *There are registered users from 80% of the utilities. 50% of registered users are active every month.*
- *At least 2 users will use the system on a daily basis, and at least 50% on a monthly basis.*

could not be assessed within the project period. The reason is that the stakeholders do not yet have access to the system due to the following reasons:

- BIOFOS decided to migrate all data and calculations/ functionalities from the existing visualization platform SAMDUS to FCF, and not only the solutions developed in DWC. This process is first completed in December 2022.
- The stakeholders have been informed about the progress and achievements for the new platform constantly at the meetings of the 'Integrated Wastewater Management Group Greater Copenhagen'. BIOFOS has though decided to first launch and give access to FCF when all functionalities are implemented, since the success rate for buy-in depends on that. A full functioning platform is crucial due to the fact that the SAMDUS visualization platform only had limited success due to performance and visualization constraints and the utilities lost interest in the system eventhough they have been part in developing it.
- To achieve a successful launch and buy- in, a 4 hours workshop is scheduled in January 2023, where DHI and BIOFOS go through FCF in detail including the forecasts and KPI-reports developed in DWC.

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10.3.2. KPI 2: Dashboards used by (top-) management

The idea with the KPI is to evaluate usability and value for (top-) management of the dashboards elaborated in DS11 and DS12. While the KPI originally was defined as "number of monthly active users" measured by tracking user behavior on the web platform, we have changed the approach to a KPI based on usability for (top-) management, to achieve engagement with the stakeholders at management level and buy in to the solutions developed.

The approach for the new KPI is consisting of conducting a usability test with selected members of management. Usability testing is the practice of testing how easy a design is to use with a group of representative users and to find out if, how, when and why they will leverage the information shown in the dashboard.

In the project the target management group for the dashboards are namely head of environmental department in BIOFOS, head of planning department in BIOFOS, head of operations in BIOFOS and chief consultant on Integrated Water Management in the associate partner HOFOR.

We were not able to conduct the usability test for the Dashboards developed in DWC, since the work on the reports has only recently been completed and the FCF platform is not launched within the organizations yet.

The usability test will be conducted in Q2/ Q3 2023, after the system has been used for a while, to understand whether it is worth generating and maintaining the developed Power- BI dashboards. As mentioned above, has BIOFOS migrated all data and functionalities from SAMDUS to FCF and needs to evaluate its return on investment.

10.3.3. KPI 3: Co- creation on functional design

The objective with a co-creation workshop on functional design is to enhance acceptance and up-take of the web-platform from the LCoP (Local Community of Practice). The requirement for the workshop was that at least one relevant employee per utility takes part in the co-creation workshop.

We covered topics, such as icons, colours etc. in the workshop under KP1. The workshop has been held 04.02.2021 with the assistance of "Icatalist" using an adapted version of a method known as the "pentagonal problem" as a basis for collecting feedback and expectations.

The KPI requirement of attendance of one member per utility in the workshop was not met, since one utility was not able to participate. Feedback was therefore collected by a meeting held between BIOFOS and the specific utility staff members of the utility.

The feedback from the utilities was considered throughout the development of functionalities within FCF, for example the display of the WWTP and effluent concentrations, see Figure 38.

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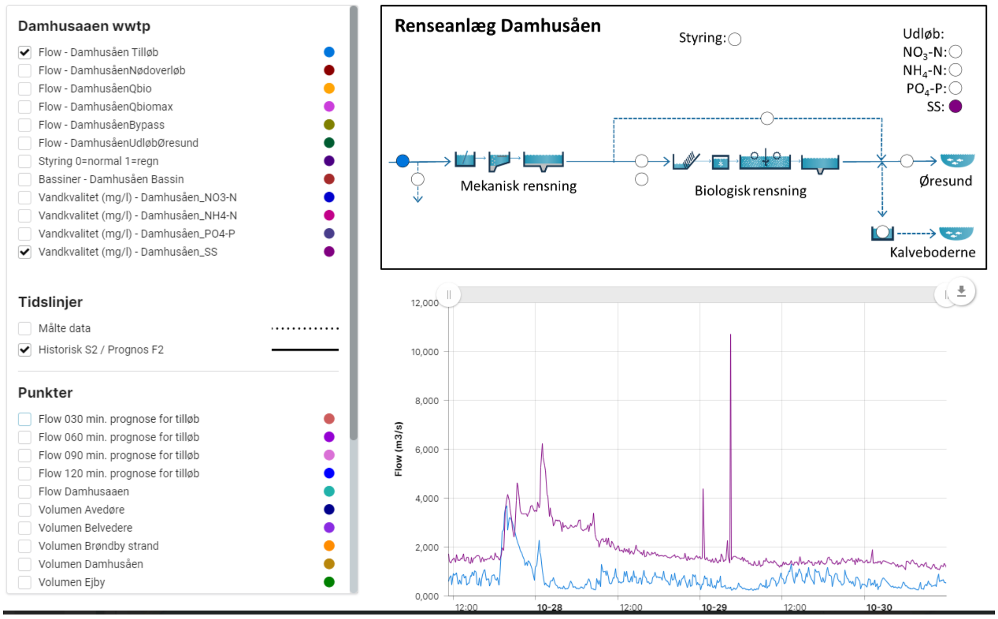

Figure 38: Sketch of the WWTP Damhusåen with its treatment steps and effluent concentrations. You can either select parameters directly in the sketch or at the item menu on the left hand. Timeseries are then displayed together. All graphs have zoom-in options.

Special focus was put into the performance of the system in fast displaying data, which was one of the main issues in SAMDUS. This issue has been successfully resolved.

10.4. Return on experience

Data communication:

The solution uses two-way communication.

- Data communication from utility to DWC platform: The solution collects data from both online sensors and gauges as well as data from SCADA systems/historian and weather data. The complete collection of flow-, level-, and volume sensor data, data from rain gauges and weather forecast data is complex as sources, communication protocols and format vary. As data is communicated via different sources and different protocols, the plan was to utilize communication standards to minimize development overhead. However, being flexible in handling data was determined to be a better approach, as no such standard exists.

- Data communication from DWC platform to utility: The DWC platform is designed to ship time series back to the utility's SCADA/historian either by the user manually downloading the selected time series in various formats or by automatic scheduling. This makes it also possible for the utilities to create relevant reports with data outside their own SCADA system.

Data acquisition:

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Retrieving historical data from offline databases at utilities was a huge effort. Likewise, it took a long time to set up data flow to maintain an updated database in the cloud. Handling big collections of data in real-time or near real-time stresses the performance of the queries when multiple users are using the system and the flow predictions are run. For that reason, there is still ongoing performance testing being carried out.

Visualization:
The FCF platform has clearly a convincing modern and intuitive visualization interface and thereby is a substantial improvement to the existing SAMDUS platform. The functionalities regarding rainfall statistics, ability to display a multiple of timeseries, dynamic, interactive, and fast zoom- in possibilities etc. are easy to access and understand. The limitations within FCF of not being able to choose icons, colors etc. as will be addressed in the further development.

Performance:
The performance/ speed to display data in FCF has been tested and evaluated a multiple of times and has surpassed BIOFOS expectations. This will thereby help to launch the platform successfully within and outside BIOFOS.

Access of external links:
FCF will not only be a visualization platform where greater Copenhagen's utilities can access each other's data but will be the platform used to communicate and share information between them. This is made possible by being able to access external links via FCF. For example, BI- reports generated within the utilities, online-tools developed with another supplier, relevant documents and project descriptions etc. The idea is to have ONE place to login and not multiple places and ONE place to access relevant information. This will make the exchange of information between the utilities more robust since we will look at the same information

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11. DS5.1: Active Unmanned Aerial Vehicle for the analysis of irrigation efficiency

11.1. Digital solution

The efficient and sustainable use of water for irrigation has become a core requirement in modern agriculture, especially in warm countries, where droughts and water stress are an issue, and in densely populated areas, where competition among water uses is on the rise. To facilitate this, a new method for the remote detection of water stress with an active Unmanned Aerial Vehicle (UAV) and multi-spectral imagery has been developed. The digital solution enables the mapping of stress conditions that is a spatially distributed phenomenon. The solution consists of the following components:

- UAV with mounted multi-spectral camera (i.e., Micasense Altum[11]);
- satellite data (Sentinel-2 and PlanetScope) provided by external providers (i.e., Sentinel-hub and Planet);
- a set of ground sensors, e.g., for measuring the volumetric water content of the soil;
- a weather station;
- irrigation systems.

UAV data are used to evaluate the crop status (nutrient and water stress) using multi-spectral data. Considering the flight costs, as well as potential restrictions (e.g., you need an authorization to fly in restricted areas), this kind of data have low temporal resolution but ultra-high spatial resolution (2-4 cm).

Satellite data are useful to evaluate the behavior of crops over a season. We use Planet and Sentinel-2 images to set-up time-series to evaluate the nutrient and water stress of crops. In this case, the temporal resolution with low cloud coverage is good (1 or 5 days), but the spatial resolution ranges from 3 to 20 m.

The *ground sensor data* is used to validate the water stress data derived from UAV and satellite data. Further, they are used as input data for agro-hydrological modelling, which simulates the dynamics of soil water content under different weather and irrigation conditions, accounting for crop development and root water uptake. The modelling allows to evaluate timing of irrigation and water volume required to satisfy the water demand of crop, information which is used as input for the Match Making Tool (DS5.2, section 12).

The *weather station* enables the calculation of evo-transpiration that is a relevant variable to identify the water need in a given time. The value of evo-transpiration could be used to predict potential water stress conditions that could occur between irrigation sessions.

Irrigation systems of course play a key-role. On the one hand, with border irrigation (low efficiency), it is important to schedule irrigation events providing the right quantity of water. On the other hand, with drip irrigation, thanks to its higher efficiency, it is possible to reduce the water footprint of the irrigation practice. Moreover, if the water is obtained from a Waste

[11] Micasense Altum - https://micasense.com/altum/ (last access Nov 2022)

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Water Treatment Plant (WWTP), fertigation with the nutrients contained in the irrigation water represents an additional advantage.

The digital solution endeavors to demonstrate the importance of data integration to make informed decisions and optimize the use of water, while reducing nutrient and water stresses.

11.2. Demo description

The digital solution has been demonstrated at the WWTP of Peschiera Borromeo, located in the eastern part of the Metropolitan City of Milan, Italy. The WWTP is surrounded by an agrarian context typical of the Lombardy Padana Plain, mainly cultivated with fodder crops (especially maize) and irrigated using traditional techniques, mainly border irrigation.

The demo site consists of a field which is 3.8 ha in size and is adjacent to the-WWTP providing water for irrigation. The field was cropped with maize during the summer season, while during the previous autumn and winter, mustard was cultivated as cover crop. Maize was sown at the beginning of April 2021, and harvesting was carried out at the end of September 2021.

We executed two flights (respectively on the 5th and 26th of August 2021) that have been authorized with specific NOtification TO AirMan (NOTAM) from the Italian Civil Aviation Authority (ENAC). The NOTAM was required considering that the demo area is located within a red area (highest risk) where UAV are not authorized to fly at any level above the ground. Processed data have ground sampling distances (GSDs) that vary from 3 to 4 cm. Flights were performed in a time window that was decided by ENAC (not under our control - 06:30-08:30 UTC) and it was not ideal due to the sun (low) elevation. Data were acquired with a lateral and longitudinal overlap of 80% at an authorized height of 25 m above the ground level due to airspace restrictions. Radiometrically calibrated orthophotos were processed using a processing pipeline inside the Agisoft Metashape Professional software. The raw and processed data are safely stored in a dedicated bucked on the Amazon Web Service (AWS) Simple Storage System (S3). Figure 39 shows the UAV set-up (drone and calibration target that is needed to have reflectance values). Further details on the solution and its technical specifications can be found in DWC-D2.4 (Technology report).

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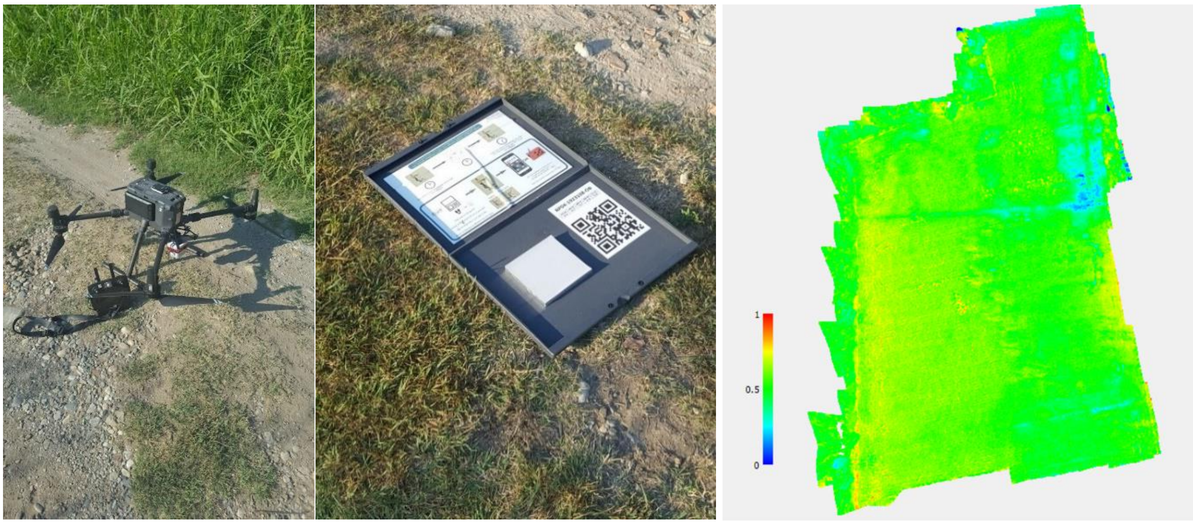

Figure 39: Left: Unmanned Aerial Vehicle on the demo area ; center: reflectance calibration target adopted to calibrate data; right: index map that reflects the crop status according to the Normalized Difference Red Edge (NDRE) Index.

Satellite data was acquired from PlanetScope and Sentinel-2 satellites to monitor the crop status. Regarding the Sentinel-2 images we processed Level-2A product. This kind of product provides Bottom of Atmosphere (BOA) reflectance images derived from the associated Level-1C products[12]. L2A images were processed using the Application Programming Interfaces (APIs) provided by the SentinelHub service[13] and stored on S3.

To obtain information about the soil water status and quality, the following ground sensors and devices were installed in the field:

- Two multilevel humidity probes, located at two points along the drippers line, which can measure the volumetric water content in the soil every 10 cm from 5 to 55 cm of depth. The probes are equipped with a modem and the data can be accessed from the cloud (Sentek Drill&Drop[14]).
- A piezometric well with a sensor to monitor the ground table depth.

Data from ground sensors (also including weather station) are stored on the cloud of service provider and a copy is also stored on the S3. The monitoring data from the ground sensors are used to validate the water stress measurements derived from UAV / satellites. In this case we consider for remotely sensed data a buffer of 10 m around the probe, and we extract the mean and mode values. These are then compared with the mean and mode values of the probes in a temporal window [t0 -T, t0] where t0 refers to the acquisition time of the satellite / drone. In addition, a weather station [ATMOS41, METER ENV.[15]] was installed near the demo

[12] Sentinel-2 Product Specifications https://sentinel.esa.int/documents/247904/685211/Sentinel-2-Products-Specification-Document (last access Nov 2022)

[13] SentinelHub API - https://www.sentinel-hub.com/develop/api/ (last access Nov 2022)

[14] Sentek Drill & Drop - https://sentektechnologies.com/product-range/soil-data-probes/drill-drop/ (last access Nov 2022)

[15] Meter Environment ATMOS 41 https://www.metergroup.com/environment/products/atmos-41-weather-station/ (last access Nov 2022)

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site to measure the local weather agrometeorological variables required to estimate crop evapotranspiration; for security reasons the station was installed inside the WWTP, about 500 m from the field. These data are available through API. These data were used to understand the need of water at a given time / crop development stage; this information could be used to select the best period to acquire data using drones and -where possible- satellites.

Traditionally, the field has been irrigated using border irrigation, with a centrifugal pump that lifts the water from a canal and conveys it to the field. In the 2021 season, a drip irrigation system was installed on one half of the site. The main pipe of the drip irrigation system starts from the outlet of the WWTP Line 2 and reaches the boundary of the field where a manifold is connected. The irrigation system is divided into four different-sectors, which are activated through four electro-valves. Each sector was irrigated for 12 hours every 2 days during the agricultural season. Laterals connected to the manifold were installed in the crop inter-row just before the beginning of the season, with a spacing of 1.4 m and were partially buried; the emitters' distance and discharge are respectively 30 cm and 1.14 l/h, thus providing an irrigation intensity of 2.7 mm/h. Figure 40 shows the demo site and main related components.

Figure 40: Overview of demo site (left), drip irrigation system installation (center), piezometer, water content probe + GSM modem, porous cups (right).

The field located immediately in the south of the experimental one was monitored and used as benchmark for the following DS (DS5.2 Match-Making Tool). It is approximately 8.5 ha in size, cultivated with maize and watered with border irrigation using a centrifugal pump powered by a tractor. Irrigation is scheduled according to a fifteen-day conventional rotation imposed by the irrigation consortium. Irrigation events were monitored to evaluate irrigation volumes and energy consumption. Ground sensors (i.e., three water content probes, a piezometer) were installed to monitor soil water status in the field.

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11.3. Assessment of the digital solution

The benefits of the solution have been assessed via defined key performance indicators (KPI). The results are summarised in Table 24. Details on the input data considered, as well as on the calculations, are given in the subsections below.

Figure 41 shows how the *Seasonal Local Water Stress* changes over the reference period (; white curve represents the average value inside the demo site while the gray area shows the 10th and 90th percentiles). Data are obtained from the processing of the Sentinel-2 L2 product with a cloud coverage lower than 30%. It is possible to show that during the agronomic season May – September the variance tends to have low values due to irrigation. It should be necessary to keep the variance as low as possible. A right management of crop should avoid water stress also distributing water to keep where possible low the variance of the SLWS index.

The raster (stress) map (Figure 42, left) related to the SLWS KPI reflects the performance of crop-soil system; this performance is not static over the season and the farmer could re-schedule the irrigation to reduce the water stress. UAV, satellite, and ground sensor data support the farmer to take decisions to reduce the stress. Figure 42, right, is related to the nutrient stress evaluated through the SLNS. Also, in this case the farmer could take actions to reduce the nutrient stress (e.g., changing the fertigation scheme, variable rate treatments, etc.).

Table 24: Overview table of KPI assessment

KPI	Short description	Quantification
Seasonal Local Water Stress (SLWS)	KPI that shows for each area of a field the level of water stress over a time-window. The data used to evaluate the water stress are acquired using UAV, SATs and ground sensors.	Raster maps of seasonal water stress (maps derived from thermal and optical data). The map could be used to change the scheduling of irrigation system (increase the amount of water)
Seasonal Local Nutrient Stress (SLNS)	KPI that shows for each area of a field the level of nutrient stress over a time-window. The data used to evaluate the nutrient stress are acquired using UAV, SATs and ground sensors.	Raster maps of seasonal nutrient stress (maps derived from optical data). The map could be used to change the level of nutrients also in case of fertigation or variable rate where available.

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KPI	Short description	Quantification
Monitoring Performance (Efficiency, quality, velocity, and cost)	Evaluation of the spatio-temporal coverage of a field to monitor the nutrient and water stress that also considers the overall cost and data quality. The comparison puts in evidence the gain over a baseline scenario that is represented by visual assessments	Gain of digital solution over the visual assessment (VS): of a field: 100% Gain of digital solution over the visual assessment (VA+GS) + ground sensors of a field: 43%

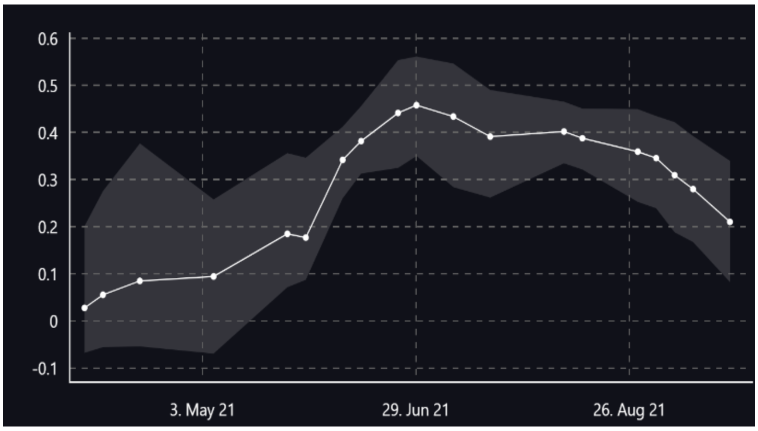

Figure 41: Evaluation of the Normalized Difference Moisture Index over a 6-month time span (last point is 23 Sept 2021).

Figure 42: Left: evaluation of the Seasonal Local Water Stress (20th Jul 2021). Right: evaluation of the Seasonal Local Nutrient Stress (20th Jul 2021).

Figure 43 shows how the yield is influenced by the combination of water and nutrient stress. In the worst case (no irrigation and no fertilization), the final yield is 1.7/ha while in the best case (irrigation with 100% of evapotranspiration and high nitrogen rate 350kg/ha) the final yield could reach the value of 6.8t/ha (4 times more than in the worst case). It is clear how the

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maps derived from UAV and satellites could help the farmer to reduce as much as possible the water and nutrient stress to optimize the final yield (data obtained from a trial in a dedicated test field to evaluate how irrigation and nutrient impact on the final yield). I0, I1 and I2 and F0, F1, F2 and F3 are levels of irrigation (0, 50 and 100% of evapotranspiration) and fertilization, mainly Nitrogen, (0, 65, 225 and 340 and kg/ha) respectively.

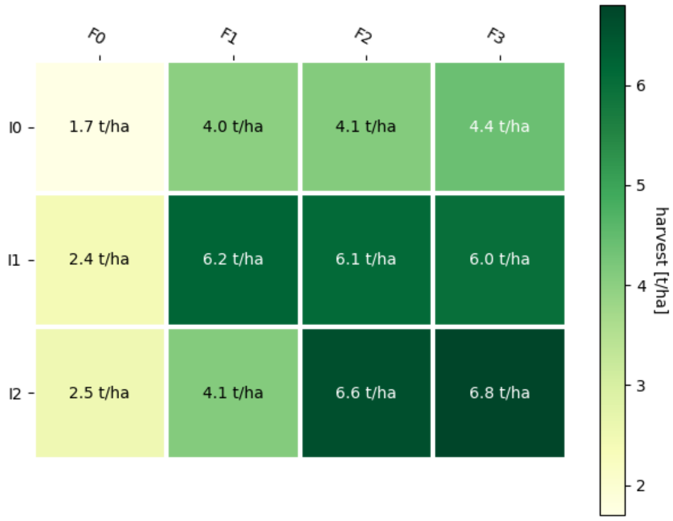

Figure 43: Effect of water and irrigation stress on the final yield.

11.3.1. KPI 1: Seasonal Local Water Stress (SLWS)

The effectiveness of crop irrigation can be influenced by several factors (e.g., soil, slope, availability of water, malfunctions of the irrigation system). In this context, appropriate monitoring plays a key role to avoid stress conditions that could negatively impact the final yield. The evaluation highlights the internal uniformity of the field in terms of water stress and provides a *normalized dimensionless value* that quantifies the water stress (as in the case of several indexes such as the Normalized Difference Vegetation Index, the Normalized Difference Red Edge, etc).

Thermal index

Using UAV and multi-spectral data it is possible to determine the actual water stress using the thermal band. We refer to the Crop Water Stress Index (CWSI). This index measures the transpiration rate of a crop on a scale from 0 to 1, by estimating the canopy temperature and the vapor pressure deficit. When the temperature of the leaf exceeds the air temperature by 4 to 6 °C, the resulting number is closer to 1 and the plant is defined to be under water stress. A CWSI of 0 corresponds to a well-watered crop with a dry soil background, while 1 represents a water-stressed crop. We decided to use ICWSI (1 – CWSI). In this case, values close to 1 represent a well irrigated crop while a value close to 0 represents a potential stress condition.

Optical Index

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Using satellite data, water stress is evaluated through the Normalized Difference Moisture Index (NDMI). This kind of index has been selected by ESA as a spectral index which is particularly sensitive to the water content of the vegetation. This index relies on the NIR band and a SWIR band.

$$NDMI = \frac{R_{NIR\ 865\ nm} - R_{SWIR\ 1610\ nm}}{R_{NIR\ 865\ nm} + R_{SWIR\ 1610\ nm}}$$

The combination of the NIR with the SWIR removes variations induced by the leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content. The water stress is also related to the Normalized Difference Vegetation Index that could be calculated using satellite and UAV data. The value range of the NDMI is -1 to 1. Negative values of NDMI (values approaching -1) correspond to barren soil. Values around zero (-0.2 to 0.4) generally correspond to water stress. High, positive values represent high canopy without water stress (approximately 0.4 to 1.0).

KPI Formula

In case of UAV, we use CSWI as the index. In case of satellites, we use NDMI as the index. We calculate the Seasonal Local Water Stress (SLWS) as it follows:

$$SLWS(i,j) = \frac{1}{count(S1,S2)} \sum_{t=S1}^{S2} index(i,j)_t - \overline{index_t}$$

i and *j* are the longitude and latitude of a given pixel within the area of interest, and *S1* and *S2* identify the reference period; *count* is a function that returns the number of acquisitions in the selected period. $\overline{index_t}$ represents the average performance on the field at time t. High values of *SLWS* identify low water stress conditions. More details regarding the time-series analysis are discussed in the references given in Pesaresi et al. (2020a and 2020b)[16, 17]. This index shows the stress over the field considering that typically there is not a single number to evaluate the performance of the field. The performance is specific for each location (pixel).

11.3.2. KPI 2: Seasonal Local Nutrient Stress (SLNS)

Using satellite and UAV data, nutrient stress is evaluated through the Normalized Difference Red Edge Index (NDRE). This kind of index has been selected considering its high sensitivity to nutrient stress (nitrogen). This index relies on the NIR and Red-Edge bands and it is calculated as it follows:

$$NDRE = \frac{R_{NIR} - R_{RED\ EDGE}}{R_{NIR} + R_{RED\ EDGE}}$$

[16] Pesaresi, S.; Mancini, A.; Casavecchia, S. (2020): Recognition and Characterization of Forest Plant Communities through Remote-Sensing NDVI Time Series. Diversity, 12, 313. https://doi.org/10.3390/d12080313

[17] Pesaresi, S.; Mancini, A.; Quattrini, G.; Casavecchia, S. (2020): Mapping Mediterranean Forest Plant Associations and Habitats with Functional Principal Component Analysis Using Landsat 8 NDVI Time Series. Remote Sens., 12, 1132. https://doi.org/10.3390/rs12071132

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KPI Formula

We calculate the Seasonal Local Nutrient Stress (SLNS) as it follows:

$$SLNS(i,j) = \frac{1}{count(S1,S2)} \sum_{t=S1}^{S2} index(i,j)_t - \overline{index_t}$$

i and *j* are the longitude and latitude of a given pixel within the area of interest, and *S1* and *S2* identify the reference period; *count* is a function that returns the number if acquisitions in the selected period and index is the NDRE. $index_t$ represents the average performance on the field at time t. High values of *SLNS* identify low nutrient stress conditions.

11.3.3. KPI 3: Monitoring Performance (Efficiency, quality, velocity and cost)

The digital solution relies on different data-sources. The best solution optimizes a cost function that considers different features as data quality, spatial resolution, samples /ha, cost/ha. In the following table we provide ranking (from 1 to 5, where 1 means bad performance and 5 optimum) of different technologies also providing the ranking of our digital solution.

Spatial resolution reflects the capability to capture variability in a given (spatial) area of a field. Of course, remote sensed platforms (e.g., aerial vehicles) have better spatial resolution if compared with ground sensors that provide accurate and precise data even if strongly local. Regarding the temporal resolution of course ground sensors output data with periods from 1 to 60 mins. Satellites are able to acquire data within the range of 1-10 days even if weather conditions and elevation of sun (related to acquisition time) have negative impacts. Satellites are able to cover area (order of km^2) while drones could cover areas up to 200-300ha / flight[18].

Table 25: KPI assessment for DS5.2 to evaluate the efficiency, quality, velocity and cost of our digital solution over reference approaches.

	Visual Assessment	**Ground Sensor**	**Fixed-wing aerial vehicle**	**Rotary-wing aerial vehicle**	**Low res SAT (GSD 30m+)**	**High res SAT (GSD <30m)**	**Our digital solution**
Data quality	2	5	5	4	4	4	**4**
Spatial Resolution	1	1	4	5	2	3	**5**
Samples / ha per week	1	5	2	2	3	3	5
Cost / ha	1	2	3	2	4	4	4

[18] fixed wing drones can map 200-300ha (indicative value for a single flight); of course the coverage is related to the flight altitude / desired ground sampling distance; rotary wing drones instead due to constraints on batteries could map smaller areas in the order of 10-20ha (indicative value) per flight.

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Upfront-cost	5	2	1	2	3	3	2
Score	**10**	**15**	**15**	**15**	**16**	**17**	**20**

Data quality plays a key role to ensure that digital solution is working on scientific data. Visual assessment embeds the experience of the observer (e.g., agronomists) but could be impacted by bias / experience. The use of sensors and more in general of scientific payloads ensures high-quality data. A relevant aspect is also related to the calibration. Period maintenance of sensors (especially probes installed inside the soil) is required to avoid errors during the measurement process. Our digital solutions integrate different technologies such as ground sensors, unmanned aerial vehicles and satellites. The combined use of different technologies has positive impact if compared with Visual Assessment (VA) or Visual Assessment + Ground Sensor (VA+GS) that are the most common scenarios in agriculture. If we consider the two reference scenarios the gain of our digital solution is calculated as the ratio between the score of our digital solutions (see previous table) over the score of baseline scenarios. To calculate the performance of VA+GS we consider the max value of Data quality, Spatial Resolution, Samples / ha per week between VE and GS while we consider the min for Cost / ha and Upfront-cost (score = 14). The score of our digital solution is double respect to the VA scenario while is 1.43 if compared with the VA+GS.

The gain of our digital solution over the VA scenario is 2 while over the VA+GS calculated is 1.43. The digital solutions rely on different data-sources and equipment with an impact on the cost of solution. However, the cost of the digital solution must be related with the potential loss of yield that could occur if visual assessment is not regularly performed and/or if the ground sensors deployed on the field are unable to capture dynamics due to low density (low number of devices).

11.4. Return on experience

The experimental application of drones, satellites, and ground sensors to monitor water stress highlighted opportunities and issues.

An important aspect to consider is the potential to gather data offered by using Unmanned Aerial Vehicles. The demo area (Peschiera Borromeo) is located nearby the Milano Linate Airport (LIML ICAO code) and the test field was in a red area where flights are not allowed. For this reason, it is necessary to apply for NOTAM and account for several potential restrictions such as the maximum altitude above the ground level (in that area ENAC authorized 20 m). In peri-urban areas it is necessary to consider these constraints that limit the capability to acquire data. By flying at 20 m, it is possible to obtain ultra-high-resolution images, but it is necessary to fly for longer times considering the flight altitude and the camera performance (it is necessary to fly at 2-3 m/s at 20 m to avoid blurring effects also ensuring a good overlap among images, which is a key factor to generate the final ortho-photo).

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The digital solution enables the mapping of stress conditions that is a spatially distributed phenomenon. The end-user could adapt the irrigation and check the effect by evaluating the KPI over a given temporal range (not necessary the overall season).

The capability to monitor the crop using drones, satellites, and ground sensors (as done in this digital solutions) represents a key component that is discussed in the following digital solutions (DS5.2). The identification of water stress and more in general the crop status could be used to support the Insurance Providers (IP) if a Notice of Loss (NoL) is opened by a farmer. For high value crops or in case of large fields (100ha+) insurance is a common way to avoid loss of profit and monitoring systems are necessary to optimize the agronomic operations.

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12. DS5.2: Match-making tool between water demand for irrigation and safe water availability

12.1. Digital solution

Currently, in many regions, treated waste-water is often discharged into rivers or even directly into existing agricultural networks and then used by farmers for irrigation as an addition to the available freshwater. Such practice, however, does not maximize the added value of the treated water due to the dilution effect. Moreover, a tool that matches the availability of water from the WWTP with the end-users (farmers) needs, both in terms of quantity and quality, would be crucial for maximizing treated waste-water reuse benefits. Our DS5.2 aims to fill this gap.

Specifically, the Match Making Tool (MMT) is a web app that visualises and matches the requirements of the different stakeholders involved in the water reuse practice. It integrates data from farmers, online services (weather), sensors and the WWTP. This digital solution is linked to the topic of sustainable and safe water-reuse in agriculture. In fact, the MMT is designed to find a *match between water demand for irrigation and safe water availability*. According to the regulation on the minimum requirements for water reuse, the crop type and irrigation method determine the water quality class needed, which in turn determines the treatment technology that should be used and its required performance, as well as the operations carried out by the water utility and reclamation facility operator. Therefore, the matchmaking tool will support several key stakeholders: the utility, the reclamation facility operator, the irrigation network operators and the farmers. DS5.2 is based on the integration of different data to map, match and monitor the different user needs.

The Match Making Tool interacts with the end-user with a reduced and user-friendly interfac e. The front-end development is inspired by the modern material design approach trying to engage the user with a UI/UX that is similar to other widespread applications. The following data are managed by the MMT:

- **Weather information**
    - Forecasts are derived from external web-services.
    - Consolidated time series are obtained from local weather stations.
- **Crop & Soil** parameters and field locations
    - Farmers provide static data such as the location of their field and the field area. This data will be provided at the beginning of the season.
    - Farmers have the option to specify the soil parameters. In case they don't provide any information, ancillary data from a geo-database are used instead. Crop details are also required, specifically, crop type and seeding/emergence date.
    - Farmers also provide details regarding their irrigation system (e.g., surface, sprinkler, drip, …)
    - Farmers could also provide dynamic data such as the crop development stage; this would allow for a more accurate estimation of irrigation needs.

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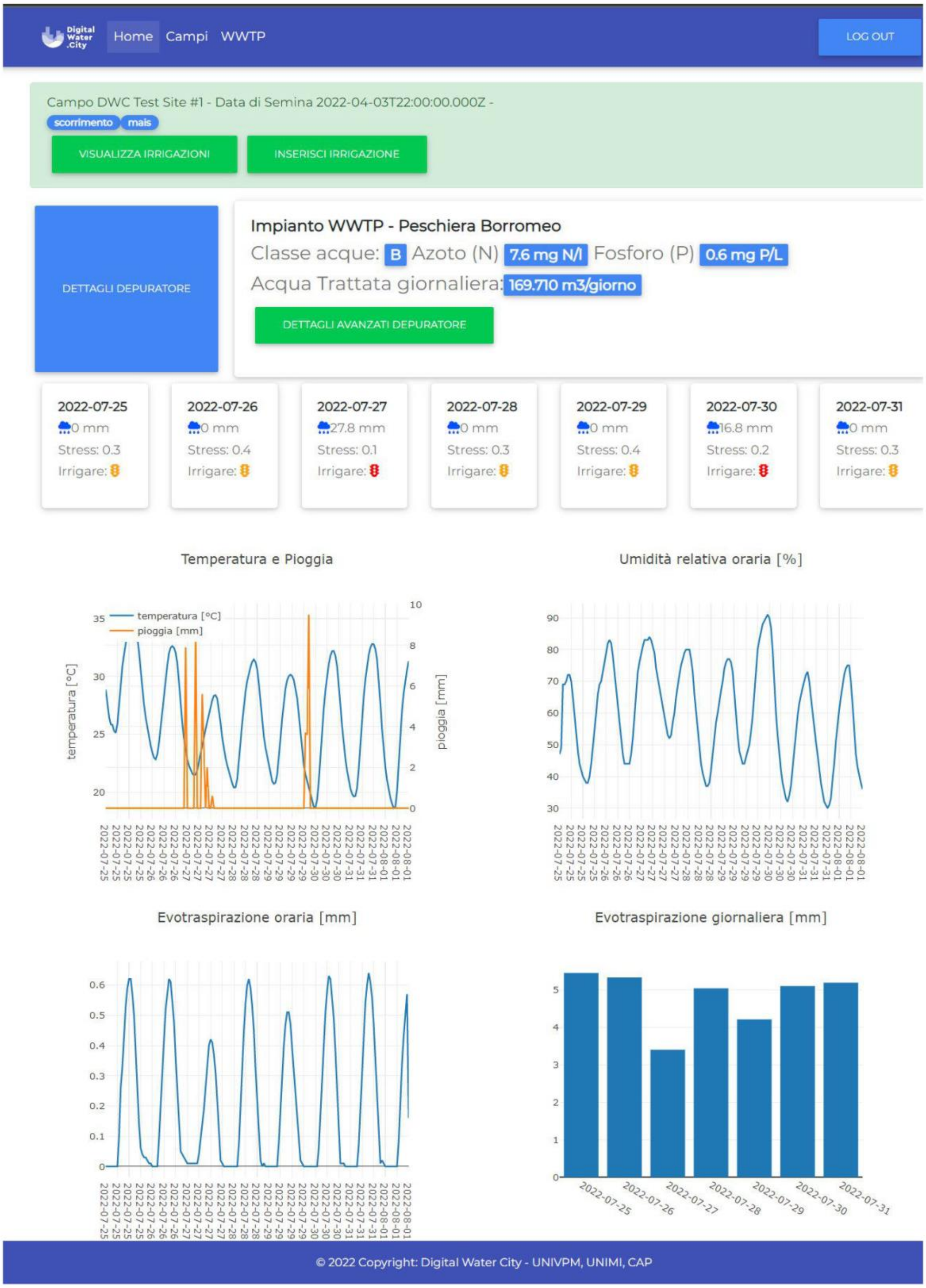

Figure 44: UI of the MMT – farmer view

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These data are pre-processed using the Soil Water Atmosphere Plant (SWAP) software[19], which was adapted to run in a *dockerized* environment, considering that the back-end of the MMT runs in a serverless environment. SWAP simulates the transport of water, solutes and heat in unsaturated/saturated soils. SWAP enables the simulation of flow and transport processes at the field scale, during growing seasons over long periods. It offers a wide range of possibilities to address both research and practical questions in the domains of agriculture, water management and environmental protection. The serverless function is triggered by the front-end through a REpresentational State Transfer (REST) Application Program Interface (API) considering the field of interest and the optional data provided by the farmer, such as the crop development stage. The output of the developed function consists of the water needs for the following days.

Another relevant aspect behind the MMT is the link with the WWTP: farmers can check if treated waste-water is available for reuse and its related water class in real time. Figure 44 gives an indication of the information provided by the MMT for a set of fields next to a given WWTP.

12.2. Demo description

In a first phase, the MMT is tested with designated test-users at the Peschiera Borromeo site, which is the same test area as for DS5.1 (Chapter 11). In a second phase, the MMT is delivered to all interested local farmers to establish a smart irrigation community (see Figure 45); they will be able to provide basic information such as the crop type, details on their irrigation practice, seeding date, and few other easily-accessible data. The MMT could be used within the whole district of Peschiera Borromeo (although of course, farmers would not obliged to follow the irrigation advice provided by the MMT).

Farmers could benefit from the use of this tool also without treated waste-water reuse, considering that the sources of water are different (e.g., in case a farm doesn't have a WWTP nearby and there is no capability to sink reused water). Data from the WWTP are collected from the CAP control room through Message Queue Telemetry Transport Secure (MQTTS). The weather station is placed inside the WWTP, and data are available by using REST API. These data are shared through the MMT for supporting end-users' decisions. Information from the Early Warning System developed in the context of DS3 (Early Warning System for safe reuse of treated waste-water for agricultural irrigation) and the quality of water play a key role to inform if the water is safe to be used to irrigate a given field using water from the WWTP.

[19] Soil Water Atmosphere Plant (SWAP) - https://www.swap.alterra.nl/ (last access Nov.. 2022)

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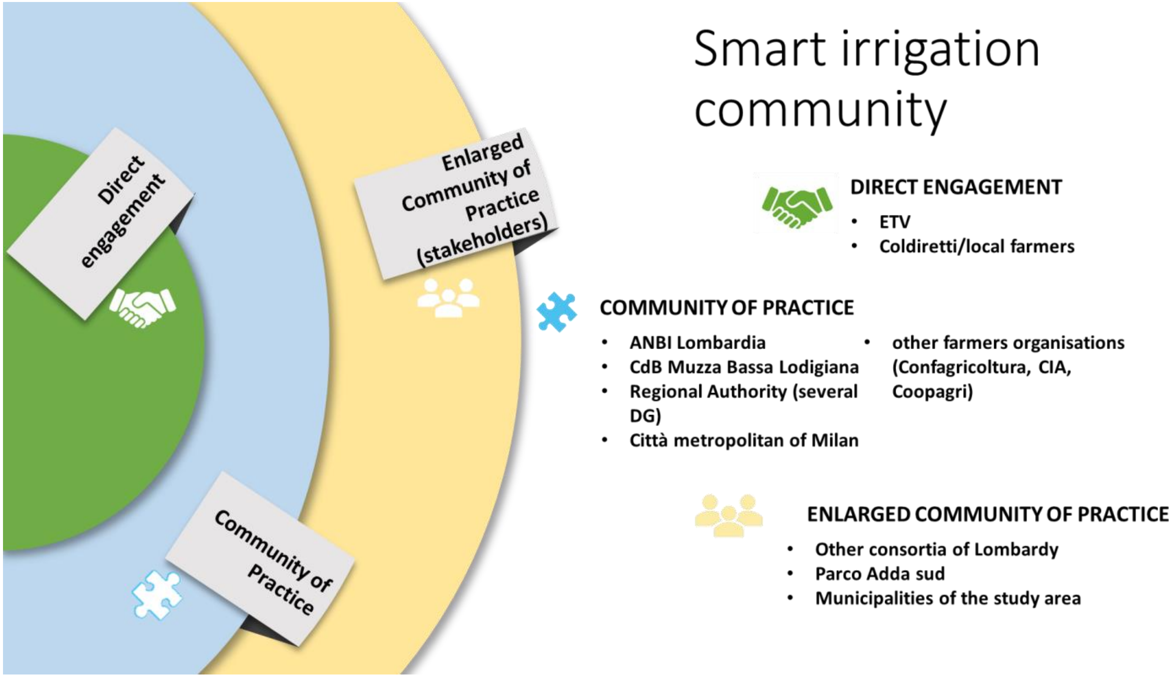

Figure 45: Smart Irrigation Community that is involved in the MMT

12.3. Assessment of the digital solution

The benefits of the digital solution were assessed via three performance indicators (KPIs; Table 26) which represent the water, fertilizer and CO2 savings offered by two scenarios that use treated waste-water through drip irrigation, vs. a baseline scenario representing the current standard practice (i.e. border irrigation with freshwater). Details of the scenarios are as follows:

- Baseline (S0): border irrigation provided by pumping water for a fixed time and interval from an open channel fed by a river diversion (typical scenario adopted by farmers), using a pump powered by a tractor to lift water from the channel (Figure 46).
- Precision drip irrigation using the MMT (S1): drip irrigation where, every day, the amount of water from the WWTP (to be) provided is estimated by calculating the hydrological balance (daily time step) using the hydrological model included in the MMT (specifically, the Soil-Water-Plant-Atmosphere (SWAP) model, developed by the University of Wageningen and widely applied to study and manage the irrigation of different crops, including maize). The irrigation event is set to start when the total soil water content in the root zone falls below a given threshold (specifically, 60% of the crop Readily Available Water (RAW), which is a common criterion for maize irrigation). The water depth provided is the amount needed to restore the soil field capacity and calculations are performed for three soil types, i.e., medium, fine and coarse texture.
- Standard drip irrigation (S2): drip irrigation where a fixed month-specific amount of water from the WWTP is provided every day (specifically, 10 mm for June and August, and 15 mm for July).

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Figure 46: border irrigation (left) vs. drip irrigation (right) at Peschiera Borromeo.

Table 26: Overview table of KPI assessment for DS5.2

KPI	Short description	Quantification
Saved Water [%] and [mm]	This KPI can be calculated either as a ratio of saved water OR as the saved water volume (i.e. absolute value) compared to the baseline scenario.	• S1: 68% of saved water compared to baseline (513 mm) • S2: 29% of saved water compared to baseline (223 mm)
Saved Fertilizer [%] and [kg/year]	This KPI can be calculated either as a ratio of saved nitrogen (i.e. nitrogen from the reuse of treated waste-water vs. nitrogen needed from standard fertilizers using a standard rate for the crop under examination) OR as an absolute value (i.e. difference between nitrogen provided as top-dressing and nitrogen provided through fertigation).	• S1: 48% of saved fertilizer compared to the baseline (37 kg/ha) • S2: 100% of saved fertilizer compared to the baseline (4 extra kg/ha)
Saved CO_2 [kg/yr]	This KPI can be calculated as the difference between the CO_2 produced under the baseline scenario and the two re-used water scenarios.	• S1: 6802 kg of saved CO2 compared to the baseline • S2: 6911 kg of saved CO2 compared to the baseline

Details on input data and calculations are given in the following subsections.

12.3.1. KPI 1: Saved Water

The KPI can be calculated either as a rate or as an absolute value.

In the former case, we calculate the Rate of Saved Water (RSW) as follows:

$$RSW = \frac{DW}{OAW} * 100 \quad (\%)$$

Where:

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DW is the amount of water provided from the WWTP; OAW is the Overall Amount of Water required by the crop over the season. In the latter case, we calculate the Absolute value Saved Water (ASW) as the difference between the amount of water provided under the baseline scenario ($S0$) and that provided through drip irrigation (Sx, where x can be either scenario 1 or 2):

$$ASW = V_{S0} - V_{Sx}$$

Where:

V_{S0} is the yearly volume (mm) provided through border irrigation ($S0$) calculated based on pump discharge for border irrigation (m^3/h), hours of pump functioning for irrigation *I* (h), and number of border irrigation events over the year;

V_{Sx} is the yearly volume (mm) provided by pump in scenarios $S1$ and $S2$, calculated based on pump discharge for drip irrigation (m^3/h), hours of pump functioning for drip irrigation in day *d*, the number of drip irrigation systems.

Results for the first season examined are:

- **Baseline:** 758 mm (considering the sum over 3 irrigation events: 243 mm + 300 mm + 215 mm).
- **S1:** 245 mm (taking the average across the 3 soil types: medium texture: 252 mm, fine: 172 mm, and coarse: 310 mm).
- **S2:** 535 mm.

12.3.2. KPI 2: Saved fertilizer

The difference in the use of fertilizer between the baseline ($S0$) and scenarios $S1$ and $S2$ concerns nitrogen only. In fact, the basal dressing before sowing has been the same for all scenarios, whereas post-emergence top-dressing has been applied for the baseline scenario only. Such fertilization scheme is a standard for the crop under examination (i.e., corn).

As for saved water, also the fertilizer-associated KPI can be calculated as a ratio or as an absolute value.

On the one hand, we calculate the Ratio of Saved Fertilizer (RSF) as the ratio between the amount of nitrogen provided through the re-used water over the season ($\mathrm{NFW_{Sx}}$) and the amount that needs to be provided using standard fertilizers over the season (NFF) using a standard rate for corn:

$$RSF = \frac{\mathrm{NFW_{Sx}}}{\mathrm{NFF}} * 100 \ \ (\%)$$

On the other hand, we calculate the Absolute value Saved Fertilizer (ASF) as the difference between the nitrogen amount provided as top-dressing and that provided through drip irrigation using water from the WWTP over the season:

$$\mathrm{ASF} = \mathrm{NFF} - \mathrm{NFW_{Sx}} \text{ (kg/year)}$$

Where:

NFF is the amount of nitrogen provided within the baseline scenario ($S0$) through top-dressing[20] over the season (kg/year).

NFW_{Sx} is the amount of nitrogen provided through the treated waste-water within scenarios $S1$ and $S2$ over the season (kg/year).

Results of provided N amounts to the field are summarized as it follows:

- **Baseline:** 70 kg/ha as top-dressing
- **S1:** 36 kg/ha from treated waste-water
- **S2:** 74 kg/ha from treated waste-water

Therefore, related KPIs for the first season are:

- S1: 49% (36 kg/ha) of saved fertilizers
- S2: 104% (4 extra kg/ha) of saved fertilizers

It should be noted that estimation of these KPIs can be refined by further considering the different efficiency in using N units in the case of top-dressing and fertigation.

12.3.3. KPI 3: Saved CO2

The CO_2 produced within the baseline scenario ($S0$) comes from:

- Fuel consumption of the tractor required for the functioning of the pump
- Top-dressing nitrogen supply

The CO_2 produced within the drip irrigation scenarios ($S1$and $S2$) comes from:

- The WWTP activity to supply the crop water demand through drip irrigation (currently neglected)
- The energy consumption for the functioning of the pump
- The nitrogen supply with fertigation as the difference between the nitrogen supplied through top-dressing and the nitrogen provided through the drip irrigation with re-used water

The associated KPI, referred to as Saved CO2 (S_{CO2}), can be calculated as the difference between the CO_2 produced under the baseline scenario ($S0$) and the re-used water scenarios ($S1$and $S2$):

$$S_{CO2} = CO2_{S0} - CO2_{Sx} \qquad \text{(kg/year)}$$

Where:

[20] The top-dressing amount is provided once and must consider nitrogen loss due leaching and denitrification processes.

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$CO2_{S0}$ is estimated based on the hours of tractor functioning for border irrigation, the number of border irrigation operations, the tractor unit fuel consumption, the amount of CO_2 produced for fuel unit, the amount of CO_2 produced for nitrogen unit;

$CO2_{Sx}$ is estimated based on the power of the drip irrigation plant pump, the hours of pump functioning per day, the number of drip irrigation systems, the CO_2 produced per unit of energy consumed, and the CO_2 emitted per unit of nitrogen produced in case that provided through fertigation is not enough.

Results of produced CO_2 are summarized as it follows

- **Baseline** (total 7322 kg):
  - From diesel consumption 2618 kg
  - From fertilizer production: 4704 kg
- **S1** (total 520 kg):
  - CO2 produced from pump functioning: 230 kg
  - CO2 produced from fertilizer production 290 kg
- **S2** (total 411 kg):
  - CO2 produced from pump functioning: 441 kg
  - CO2 saved from fertilizer production 30 kg

It should be noted that estimation of these KPIs do not consider the emissions linked with the WWTP processes.

12.4. Return on experience

The design and development of the MMT highlighted opportunities and issues.

A possible limitation of the solution is related to the availability and quality of water from the WWTP, which has consequences and possible side effects that depend on the combination of the following main factors:

- type of crop;
- growing/development stage of the crop (week of the year / development stage according to BBCH[21]);
- meteorological conditions;
- occurrence and length of treated wastewater supply interruption.

The impacts can be minimal in case of less sensitive growing stages, low-stress meteorological conditions and short interruptions, while they can be tragic in case of crucial growing stages, high-stress meteorological conditions and long interruptions. An option that could be explored to counteract this limitation is the use of dedicated insurance contracts. The capability to acquire data regarding the management of irrigation (also including WWTP) could be used to support the Insurance Providers (IP) if a Notice of Loss (NoL) is opened by a

[21] BBCH, https://www.politicheagricole.it/flex/AppData/WebLive/Agrometeo/MIEPFY800/BBCHengl2001.pdf (last access Nov 2021)

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farmer. Data sharing is a key factor to establish a link between IPs and farmers. This aspect also reinforces the engagement of other stakeholder as the irrigation consortia and the farmer associations to establish contracts that will promote the use of digital solutions to reduce where possible the insurance premium.

Another aspect to consider is the complexity related to the integration of data from different actors such as farmers, irrigation consortia, WWTP, reclamation facility operator(s). In the Milan case study, the integration of data from the WWTP required considerable time due to several reasons (privacy, infrastructure…). However, a relevant lesson learned is the necessity to define a common way to exchange data in an efficient and safe way. The MMT, thanks to FIWARE[22], gained flexibility and robustness and can now manage the integration of data that come from the WWTP effectively.

The MMT also requires a strong interaction with end-users and all involved stakeholders (e.g., reclamation facility operator, farmer association, irrigation consortia, …). It is complex to change well consolidated approaches; the MMT aims to providing suggestions to end-users that -if considered- will enable to improve the management of water resources for irrigation.

[22] FIWARE - https://www.fiware.org/ (last access Nov 2021)

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