



**Digital
Water
.City**

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

Benefits obtained through the deployment of digital solutions
(M30 draft version)



| | |
|---------------------------|---|
| Deliverable N° 2.2 | Performance and return on investment of urban water systems |
| Related Work Package | WP2 |
| Deliverable lead | Mathias Riechel (KWB) |
| Author(s) | Adriano Mancini, Francesco Fatone (UNIVPM); Gian Battista, Claudio Gandolfi (UNIMI); Marco Bernardi (CAP); Alexander Sperlich, Michel Gunkel (BWB); Stephan Gensch (VRAGMENTS); Hella Schwarzmüller, Mathias Riechel (KWB); Remy Schilperoort (P4UW); Ricardo Gilead Baibich (KANDO); Barbara Greenhill, Dines Thornberg, Carsten Thirsing (BIOFOS); Sten Lindberg; Laura Fröhlich (DHI); Oriol Gutierrez, Silvia Busquets (ICRA); Neus Amela, José Luis Martinez (IOTSENS); George Margreiter (IPEK) |
| Contact for queries | Mathias Riechel (KWB) |
| Grant Agreement Number | n° 820954 |
| Instrument | HORIZON 2020 |
| Start date of the project | 01 June 2019 |
| Duration of the project | 42 months |
| Website | www.digital-water.city |
| Abstract | <p>The present report summarizes the benefits of the eleven digital solutions demonstrated within DWC-WP2 in the form of fact sheets.</p> <p>The document aims to help cities and water utilities in finding appropriate solutions for their operational, environmental or public health deficits.</p> <p>The report is a draft version that will be updated and published as a final version in Nov. 2022.</p> |

Dissemination level of the document

| | | |
|-------------------------------------|----|---|
| <input checked="" type="checkbox"/> | PU | Public |
| <input type="checkbox"/> | PP | Restricted to other programme participants |
| <input type="checkbox"/> | RE | Restricted to a group specified by the consortium |
| <input type="checkbox"/> | CO | Confidential, only for members of the consortium |

Versioning and contribution history

| Version* | Date | Modified by | Modification reasons |
|----------|------------|--|--|
| D1 | 2021-07-29 | Mathias Riechel | Report template with structure and intro chapter |
| D2 | 2021-10-11 | Task leaders | 1 st draft of report chapters |
| D3 | 2021-10-14 | Mathias Riechel | 1 st review (internal): commented and edited |
| R1 | 2021-11-05 | Task leaders, Mathias Riechel | 2 nd draft of report chapters, compiled to full document |
| R2 | 2021-11-16 | Kari Elisabeth Fagernaes, Rebekah Eggers | 2 nd review (external): commented and edited |
| R3 | 2021-11-24 | Task leaders, Mathias Riechel | Full report version with feedback of two external reviewers incorporated and some final comments |
| R4 | 2021-11-25 | Nico Caradot | Coordinator review |
| S1 | 2021-11-30 | Mathias Riechel | Final version with minor adaptations after last review |
| S2 | 2022-03-24 | Hella Schwarzmüller | Addressing reviewer's comments & coordinator review |

* 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.

Table of content

| | | |
|-------|--|----|
| 1 | Preface | 10 |
| 2 | DS7.1: Mobile application for data collection of drinking water wells..... | 12 |
| 2.1 | Digital solution | 12 |
| 2.2 | Demo description..... | 13 |
| 2.3 | Assessment of the digital solution | 13 |
| 2.3.1 | KPI 1: Mean time to follow-up field work at drinking water wells..... | 14 |
| 2.3.2 | KPI 2: Employee satisfaction..... | 14 |
| 2.3.3 | KPI 3: Digitalized business processes..... | 15 |
| 2.4 | Return on experience..... | 15 |
| 3 | DS7.2: Forecasting tool for strategic planning and maintenance of drinking water wells | 17 |
| 3.1 | Digital solution | 17 |
| 3.2 | Demo description..... | 17 |
| 3.3 | Assessment of the digital solution | 19 |
| 3.4 | Return on experience..... | 20 |
| 4 | DS9: Sensors and smart analytics for tracking illicit sewer connection hotspots..... | 22 |
| 4.1 | Digital solution | 22 |
| 4.2 | Demo description..... | 23 |
| 4.3 | Assessment of the digital solution | 25 |
| 4.3.1 | KPI 1: hotspot screening efficiency..... | 25 |
| 4.3.2 | KPI 2: cost reduction for hotspot screening | 27 |
| 4.4 | Return on experience..... | 28 |
| 5 | DS8: DTS sensor for tracking illicit sewer connections | 29 |
| 5.1 | Digital solution | 29 |
| 5.2 | Demo description..... | 30 |
| 5.3 | Assessment of the digital solution | 31 |
| 5.3.1 | KPI: IC detection..... | 32 |
| 5.3.2 | KPI: OPEX ratio..... | 33 |
| 5.4 | Return on experience..... | 33 |
| 6 | DS14: Low-cost temperature sensors for real-time combined sewer overflow and flood monitoring..... | 34 |
| 6.1 | Digital solution | 34 |
| 6.2 | Demo description..... | 34 |
| 6.3 | Assessment of the digital solution | 35 |
| 6.3.1 | KPI 1: Number of additional CSO events detected..... | 36 |
| 6.3.2 | KPI 2: Detection accuracy for CSO frequency-occurrence..... | 37 |
| 6.3.3 | KPI 3: Detection accuracy for CSO duration | 38 |
| 6.3.4 | Other KPI's | 38 |

| | | |
|--------|--|----|
| 6.4 | Return on experience..... | 38 |
| 7 | DS15: Smart sewer cleaning system with HD camera and wireless communication | 40 |
| 7.1 | Digital solution | 40 |
| 7.2 | Demo description..... | 40 |
| 7.3 | Assessment of the digital solution | 41 |
| 7.3.1 | KPI 1: Cleaning effort | 42 |
| 7.3.2 | KPI 2: Inspection efficiency..... | 42 |
| 7.3.3 | KPI 3: Financial value | 42 |
| 7.4 | Return on experience..... | 43 |
| 8 | DS11: Sewer flow forecast tool box..... | 44 |
| 8.1 | Digital solution | 44 |
| 8.2 | Demo description..... | 45 |
| 8.3 | Assessment of the digital solution | 46 |
| 8.3.1 | KPI 1: Improved forecast during wet weather..... | 47 |
| 8.3.2 | KPI 2: Accuracy of forecast time for dry weather – 36 h..... | 48 |
| 8.3.3 | KPI 3: Reduction of wrong automatic switching between dry and wet weather operation at the WWTP | 48 |
| 8.3.4 | Other benefits..... | 49 |
| 8.4 | Return on experience..... | 49 |
| 9 | DS12: Interoperable decision support system and real-time control algorithms for stormwater management | 51 |
| 9.1 | Digital solution | 51 |
| 9.2 | Demo description..... | 51 |
| 9.3 | Assessment of the digital solution | 52 |
| 9.3.1 | KPI 1: Reduction of annual by-pass volume [m ³]..... | 53 |
| 9.3.2 | KPI 2: Reduction of nitrogen (N) emission..... | 53 |
| 9.3.3 | KPI 3: CAPEX reduction for constructions to reduce bypass | 53 |
| 9.4 | Return on experience..... | 54 |
| 10 | DS13: Web-platform for integrated sewer and wastewater treatment plant control | 56 |
| 10.1 | Digital solution | 56 |
| 10.2 | Demo description..... | 56 |
| 10.3 | Assessment of the digital solution | 58 |
| 10.3.1 | KPI 1: Increased usage, utility buy-in..... | 58 |
| 10.3.2 | KPI 2: Dashboards used by (top-) management | 59 |
| 10.3.3 | KPI 3: Co- creation on functional design..... | 59 |
| 10.4 | Return on experience | 59 |
| 11 | DS5.1: Active Unmanned Aerial Vehicle for the analysis of irrigation efficiency | 61 |
| 11.1 | Digital solution | 61 |
| 11.2 | Demo description..... | 62 |

| | | |
|--------|---|----|
| 11.3 | Assessment of the digital solution | 64 |
| 11.3.1 | Seasonal Local Water Stress (SLWS) | 66 |
| 11.3.2 | Seasonal Local Nutrient Stress (SLNS) | 67 |
| 11.4 | Return on experience | 68 |
| 12 | DS5.2: Match-making tool between water demand for irrigation and safe water availability .. | 69 |
| 12.1 | Digital solution | 69 |
| 12.2 | Demo description..... | 70 |
| 12.3 | Assessment of the digital solution | 71 |
| 12.3.1 | KPI 1: Saved Water..... | 72 |
| 12.3.2 | KPI 2: Saved fertilizer | 73 |
| 12.3.3 | KPI 3: Saved CO2 | 74 |
| 12.4 | Return on experience | 75 |
| 13 | Final remarks and outlook | 77 |

List of figures

| | |
|--|----|
| Figure 1: The digital solutions of DWC-WP2 and their addressed domain in the water cycle. | 10 |
| Figure 2: Prototype of a dashboard as part of the progressive web app..... | 12 |
| Figure 3: Feedback from prototype workshop participants (n=5) on expected benefits of the Well Diary. | 14 |
| Figure 4: left: clogged well, ochre deposits inside the screen; right: clogged pump, ochre deposits at the pump intake, both ©BWB..... | 17 |
| Figure 5: Input data and ML model performance for the prediction of well capacity..... | 19 |
| Figure 6: KANDO's smart unit and sensor (left), the EC sensor and logger (right) as well a sensor installed at a sewer manhole (right). | 22 |
| Figure 7: Storm water catchment area of the urban lake Fennsee. | 23 |
| Figure 8: Examples for evaluation: IC likely (top), possible (middle) and unlikely (bottom). | 24 |
| Figure 9: Evaluation of the investigated measuring sites and the interpretation for hot spots..... | 27 |
| Figure 10: 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). | 30 |
| Figure 11: Overview of studied sewer system and fiber-optic cable routes (left); DTS unit installed at Bezirksamt Charlottenburg (right)..... | 31 |
| Figure 12: Example of DTS monitoring results (left); corresponding location of the suspected illicit connection (right) | 32 |
| Figure 13: Storm sewer manhole located in the middle of the street (right); preparations to realize access to the sewer system via house connection (left). | 33 |
| Figure 14: XPECTION device for smart sewer cleaning (DS15) consisting of the cleaning nozzle, the inspection camera and a control panel for visualization. | 40 |
| Figure 15: A IPEK XPECTION device for smart sewer cleaning. | 43 |
| Figure 16: 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. | 45 |
| Figure 17: WWTP inflow prediction composite model. | 46 |
| Figure 18: Relationship between bypass reduction and basin volume. For example, to achieve a reduction of 500,000 m ³ in bypass you would need a storage basin volume at the WWTP of 20,000 m ³ | 54 |
| Figure 19: Screen capture of entry page for DS13. Map overview with dynamic links to all sensor stations..... | 56 |
| Figure 20: Screen capture of a simulated inflow forecast – for a dry weather period. The site is Gothenburg, Sweden, and used as an example only. | 57 |
| Figure 21: Left: Unmanned Aerial Vehicle on the demo area to detect water stress; 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 – 5 th August 2021..... | 62 |
| Figure 22: Overview of demo site (left), drip irrigation system installation (center), piezometer, water content probe + GSM modem, porous cups (right). | 64 |
| Figure 23: Evaluation of the index (NDMI) over a 6-month time span (last point is 23 Sept 2021); white curve represents the average value inside the demo site while the gray area shows the 10 th and 90 th percentiles..... | 65 |

Figure 24: Left: evaluation of the SLWS (20th Jul 2021); green pixels are related to areas with lower stress; purple refers to areas with higher stress. Right: evaluation of the SLNS (20th Jul 2021); green-orange pixels are related to areas with lower stress; dark orange /purple refers to areas with higher stress 65

Figure 25: Effect of water and irrigation stress 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. 66

Figure 26: UI of the MMT – farmer view 69

Figure 27: Smart Irrigation Community that is involved in the MMT 71

Figure 28: border irrigation (left) vs. drip irrigation (right) at Peschiera Borromeo. 72

List of tables

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. 11

Table 2: Overview table of KPI assessment (preliminary results) 13

Table 3: Features of the “Well Diary” identified during incremental development and their state of realization 16

Table 4: Overview table of KPI assessment (preliminary results) 19

Table 5: Evaluation scheme 23

Table 6: Overview table of KPI assessment (preliminary results) 25

Table 7: Results of the measuring campaign. 26

Table 8: Overview table of KPI assessment (preliminary results) 31

Table 9: Overview table of KPI assessment (preliminary results of the period Sept 2020 -Sept 2021) 35

Table 10: Overview of the current status of the operations, attended 41

Table 11: Overview table of KPI assessment (preliminary results) 42

Table 12: Overview table of KPI assessment (preliminary results) 47

Table 13: Mean root mean square error values [L/s] for the STAR model and the new ML model (DS11) for forecast lead times between 30 and 120 min and relative increase in accuracy 48

Table 14: Overview table of KPI assessment (to be completed) 52

Table 15: Overview table of KPI assessment (to be completed) 58

Table 16: Overview table of KPI assessment (preliminary results) 64

Table 17: Overview table of KPI assessment for DS5.2 (preliminary results) 72

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.

By M30, all DS were at the stage of approaching the end of the demonstration phase. KPI were defined, but not fully assessed, yet. The deliverable will be updated by M42.

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 D2.3 Technology report (final version in M36 as D2.4)

Thus report is a draft version of the final report that will be delivered updated in M42.

Following the external review, the executive summary has been added to reflect the consideration of the comments received.

The final report (M42) will be enhanced following the reviewers’ comments by

- splitting solution-specific Return on Experience section into technological issues (developers’ perspective), financial/ economic benefits (CAPEX/OPEX) and end- users’ experience
- including more generalized return on experience to reflect on the added value of the DWC digital solutions for water infrastructure operators
- linking solution-specific KPIs to overall expected impact and project KPIs.

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 solutions¹ 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.

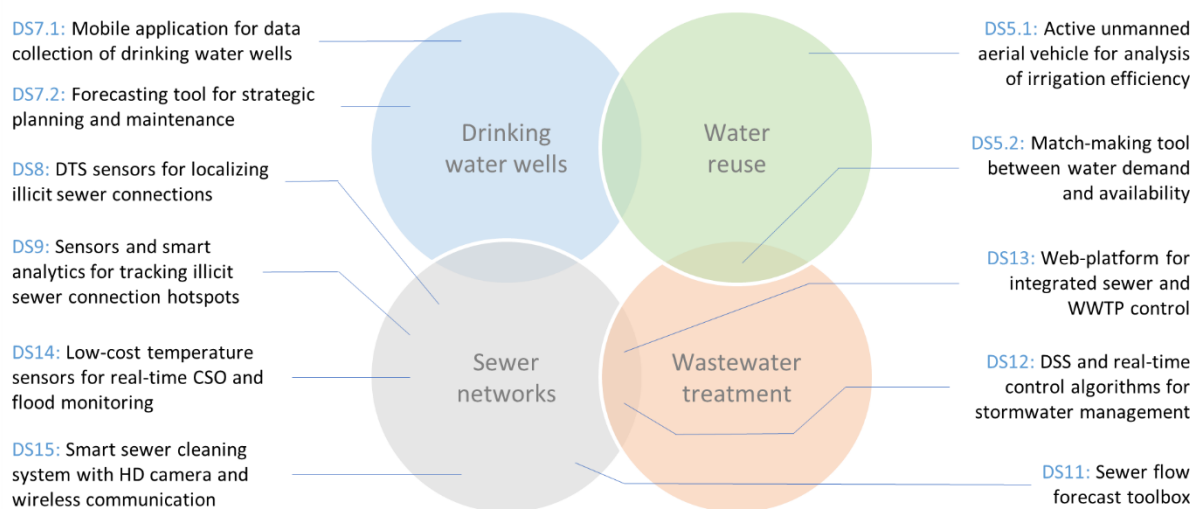


Figure 1: The digital solutions of DWC-WP2 and their addressed domain in the water cycle.

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 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.

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

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 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 D2.3 (technology report).

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

2.1 Digital solution

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. 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 "Well Diary" (DS7.1) consists of i) a user-friendly web application (frontend) accessible from mobile devices 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.



Figure 2: Prototype of a dashboard as part of the progressive web app.

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 6 smaller waterworks and form internal teams, which are responsible for operation and maintenance of wells and infrastructure in the three main waterwork-groups.

2.2 Demo description

The development of the digital solution DS 7.1 “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 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

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. These results were the basis for an assessment of the digital solutions using three defined performance indicators (KPI).

The results are summarised in Table 2.

Table 2: Overview table of KPI assessment (preliminary results)

| KPI | Short description | Quantification |
|---|--|---|
| Mean time to follow-up field work at drinking water wells | Time savings realized by the implementation of the technical solution, the average value from test user reports (rank 1-5) are a first attempt to quantify the savings. The analysis will be refined in the next months. | Average feedback from test user reports 4,4 (positive to very positive) |
| Employee satisfaction | Average value from test-user reports (rank 1-5) | Average feedback 4,4 (positive to very positive) |
| Digitalized business processes | New items in internal database to paper | Not yet available, as database items and linkage to “Well Diary” are still work in progress. Final evaluation after deployment. |

2.3.1 KPI 1: Mean time to follow-up field work at drinking water wells

Figure 9 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).

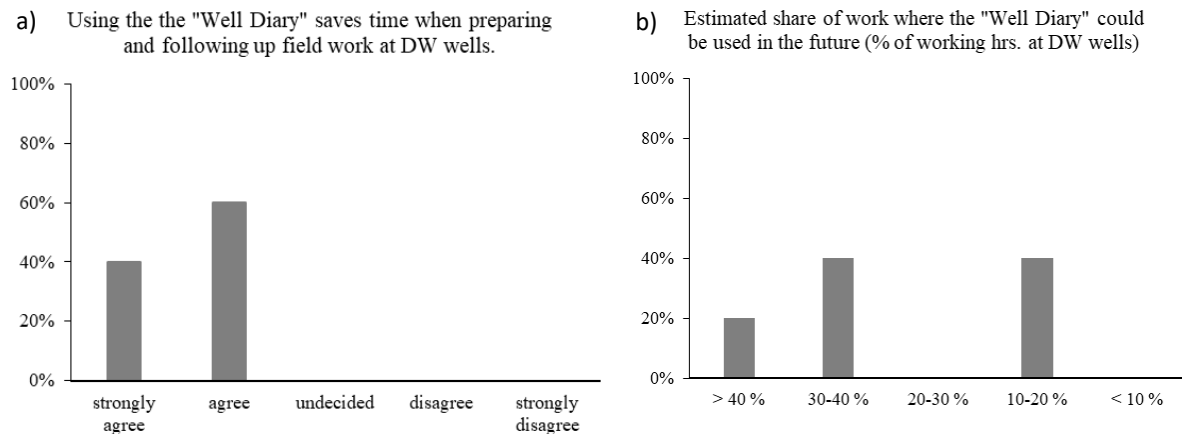


Figure 3: Feedback from prototype workshop participants (n=5) on expected benefits of the Well Diary.

Depending on data quality concerning status-quo, the required time to transfer data to the database will also be quantified using additional data after the digital solution has been deployed.

2.3.2 KPI 2: Employee satisfaction

Employee satisfaction was also assessed using data from test user questionnaires (Figure 10). The “Well Diary” is expected to increase the job appeal as well as positively influence the profession (Figure 4 a and b). Average feedback was 4.4, corresponding to an estimated positive to very positive change in job appeal.

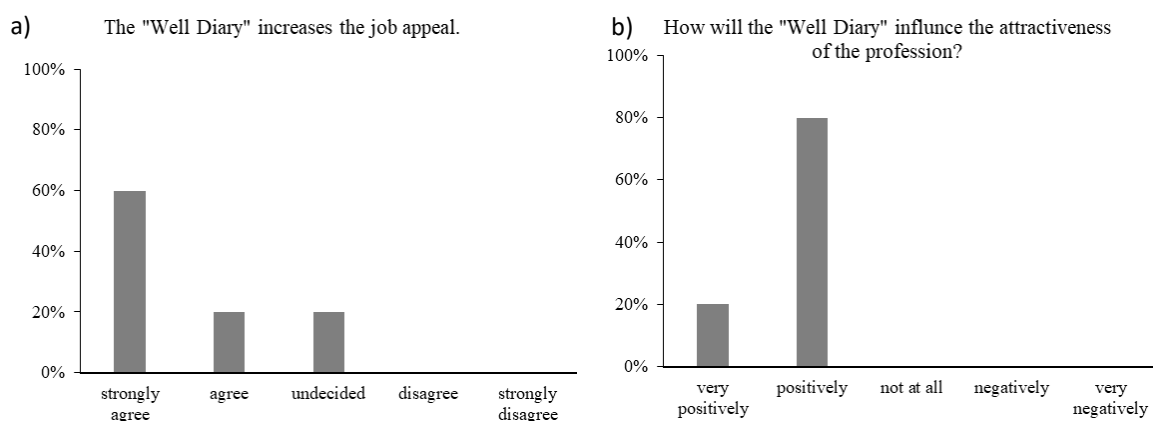


Figure 10: Feedback from prototype workshop participants (n=5) on expected benefits of the Well Diary.

2.3.3 KPI 3: Digitalized business processes

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 data base. The number of these additional data base items relates to the work processes could be used as KPI. This number will be quantified after development and deployment of the digital solution is completed (expected in early 2022).

2.4 Return on experience

The realized incremental development including early prototyping and continuous delivery enabled the user-centric development of the “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 available capacity of the project. This process also made it possible that the features could be prioritized according to end-users needs. A summary of the identified features and their state of realization is shown in Table 3. The practical needs and precise requirements of the utility end-users was made available to technology providers and enables them to tailor digital solutions and develop a business case.

However, it was also shown that standardization is a prerequisite for digitalization. Additional, unplanned effort for internal standardizing of procedure and the extension of internal databases proved to be a barrier for implementation of the digital solution. Regarding the security of critical infrastructure, the deployment into the utilities’ IT environment will be in form of a containerized solution, which has already been prepared in accordance with WP 4.

Table 3: Features of the “Well Diary” identified during incremental development and their state of realization

| Well Diary feature | State of realization | Outlook |
|---|-------------------------|--|
| show flow meter type | realized in test system | deployment planned |
| show last flow meter maintenance | realized in test system | deployment planned |
| show variable frequency drive type and specifications | realized in test system | deployment planned |
| show additional equipment (filter) | realized in test system | deployment planned |
| show date of equipment change | realized in test system | deployment planned |
| show well coordinates and link to GIS | realized in test system | deployment planned |
| show graphical symbol for variable speed pumps in well overview | not yet realized | realization and deployment prioritized |
| read maintenance documentation of variable frequency drives and transfer to internal database | not yet realized | realization and deployment prioritized |
| deployment into BWB IT, dockerization; connection to internal database | not yet realized | in progress |
| show well state | not yet realized | standardization needed, exceeds development capacity |
| read ,well state’ and transfer to internal database | not yet realized | standardization needed, exceeds development capacity |
| checklists for annual maintenance (show, read and transfer) | not yet realized | standardization needed, exceeds development capacity |
| show detailed information on well maintenance (dosage, type of chemical etc.) | not yet realized | exceeds development capacity |
| show related documentation and manuals (test protocols etc.) | not yet realized | exceeds development capacity |

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

3.1 Digital solution

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. 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 4) 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.

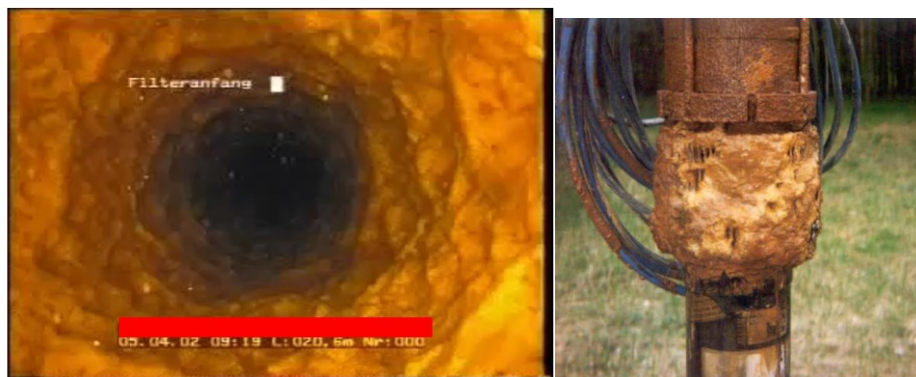


Figure 4: left: clogged well, ochre deposits inside the screen; right: clogged pump, ochre deposits at the pump intake, both ©BWB

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.

3.2 Demo description

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 sets 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 correlation² and categorical variables using the Chi-Square and Cramér's V method^{3,4}. 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.

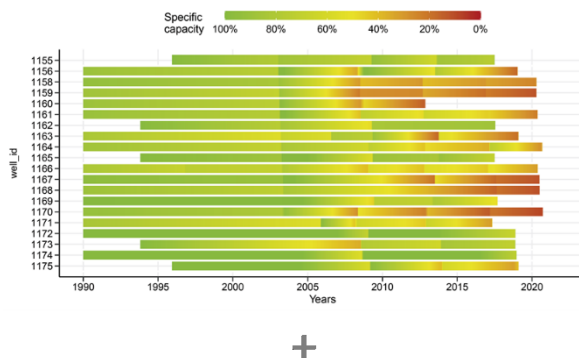
Further, five statistical and ML-based methods have been tested and compared regarding their capability to predict the specific capacity of a well (i) multivariate linear regression, (ii) logistic regression, (iii) decision tree, (iv) random forest and (v) gradient boosting. The gradient boosting model performed best, with 94% of all data points with a remaining specific capacity of below 80% predicted correctly and only 12% false warnings (Figure 5). 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.

² 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.

³ 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.

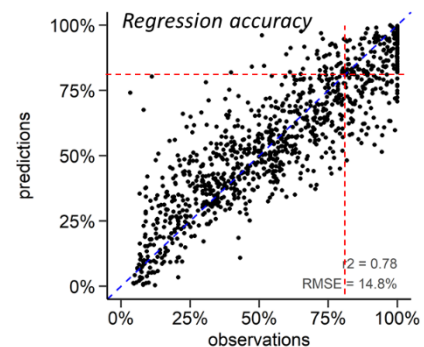
⁴ Cramér, H. (1946): Mathematical Methods of Statistics. Princeton: Princeton University Press, page 282 (Chapter 21. The two-dimensional case). ISBN 0-691-08004-6

Training data (Interpolated for visualisation)



ML model

Model performance for test data



Predictor variables (well age, number of rehabilitations, time since last rehabilitation, daily variation in abstraction volume + 21 other variables, distinguished into well characteristics, site properties and water quality data)

Classification accuracy (for critically low well capacities < 80%): 94% recall and 88% precision

Figure 5: 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. The coefficient of determination (r^2) and root mean square error (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 (preliminary results)

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

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”⁵.

⁵ R Core Team (2021) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

DS7.2 predicted values are the results of the gradient boosting model for the test data set compared with observations (Figure 5). 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 taken into account. 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. This will be discussed with BWB staff in the coming months. In parallel, transferability and commercialization potential will be assessed in the frame of WP5 with the business canvas method provided by Strane (cf. D5.1 and D5.5).

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 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. Refinement of the solution within the DWC project will 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.

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 $\mu\text{S}/\text{cm}$) and sanitary sewage (> 1000 $\mu\text{S}/\text{cm}$), 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 are changed every two to three weeks.

In case of the MP sensors, data is acquired every 5 minutes and sent to the cloud three times a day.

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.



Figure 6: KANDO's smart unit and sensor (left), the EC sensor and logger (right) as well a sensor installed at a sewer manhole (right).

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 7: 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 sewer network at key points in the system. In case of suspicious results, the sensors were iteratively relocated upstream. Until now, 15 measuring sites have been monitored throughout seven measuring phases.

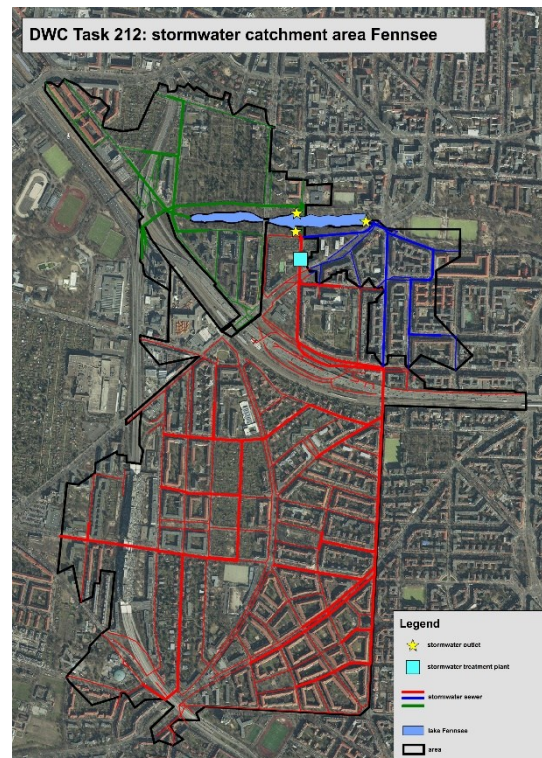


Figure 7: Storm water catchment area of the urban lake Fennsee.

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, the data of four weeks during dry weather are considered. Wet weather is defined as the time interval from one hour before to one hour after a rain event. Rain events were evaluated from a rain gauge near by the demo area. Exceedances of the limit values 700 $\mu\text{S}/\text{cm}$ and 5000 $\mu\text{S}/\text{cm}$ are considered and classified into three categories based on a traffic light system, as shown in Table 5.

Table 5: Evaluation scheme

| colour | number of peaks > 700 $\mu\text{S}/\text{cm}$ / 4 weeks | meaning |
|--------|---|--------------------------------------|
| | > 4 (or peak > 5000 $\mu\text{S}/\text{cm}$) | Illicit sewer connection is likely |
| | 2 – 4 | Illicit sewer connection is possible |
| | 0 – 1 | Illicit sewer connection is unlikely |

An example for every category is given in Figure 8. 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 700 $\mu\text{S}/\text{cm}$ 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.

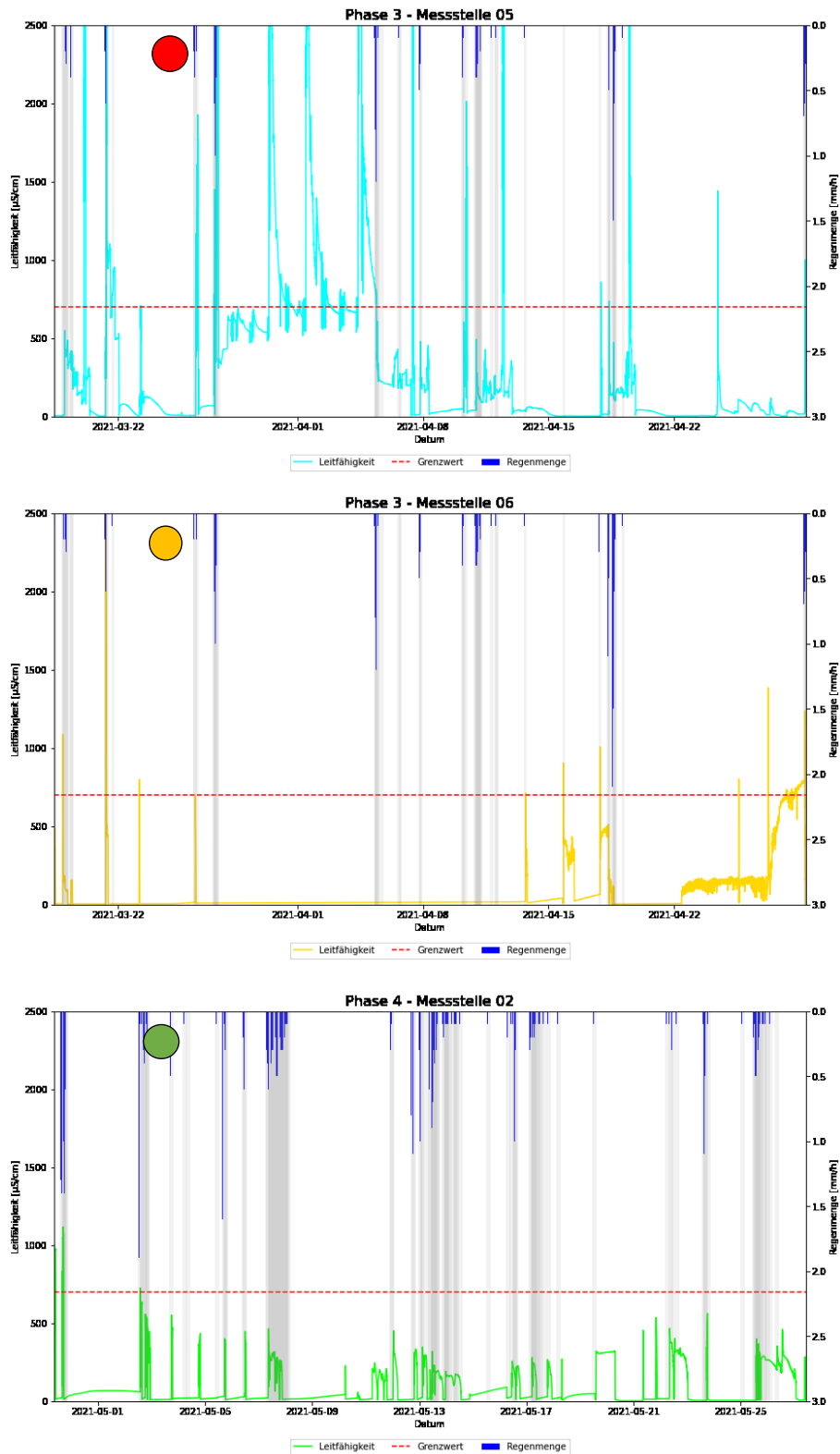


Figure 8: Examples for evaluation: IC likely (top), possible (middle) and unlikely (bottom).

To date, the hot-spot analysis is solely based on the results from the EC sensors. The data of the MP sensors and KANDO's smart unit will be integrated into the analysis in the following months.

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 2010 to 2019 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 (preliminary results)

| 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). Quotient of identified relevant sewers length by conventional visual inspections (VI) and DS 9. | $= 1 - \frac{sewer_{IC,EC}}{sewer_{IC,VI}} = 1 - \frac{25 \text{ km}}{39 \text{ km}} = 36\%$ |
| cost reduction for hotspot screening | Cost reduction for hotspot screening comparing personal costs und equipment maintenance costs for DS 9 and for conventional visual inspections (VI). | $= \frac{personal \ costs_{DS/year} + technical \ costs_{DS}}{personal \ costs_{VI/year}}$ $= \frac{\sum (personal \ time_{DS} * specific \ personal \ costs) + \sum (sensor)}{\sum (personal \ time_{VI} * specific \ personal \ costs)}$ |

4.3.1 KPI 1: hotspot screening efficiency

The evaluation of every measuring site in every measuring phase is shown in Table 7. The colour coding is similar to the scheme explained in Table 5. A grey colour means, that there have been investigations, but they could not be evaluated, for example because of technical problems.

Table 7: Results of the measuring campaign.

| | phase 1 | phase 2 | phase 3 | phase 4 | phase 5 | phase 6 | phase 7 |
|-------------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| | 29.01.21 - 18.02.21 | 18.02.21 - 18.03.21 | 18.03.21 - 29.04.21 | 30.04.21 - 27.05.21 | 27.05.21 - 25.06.21 | 25.06.21 - 13.08.21 | 13.08.21 - 16.09.21 |
| green area - northwest | | | | | | | |
| M 4 | | | | | | | - |
| M 2 | - | - | | | - | - | - |
| M 29 | - | - | | | - | - | - |
| M 30 | - | - | | | | - | - |
| M 32 | - | - | - | - | | - | - |
| red area - south | | | | | | | |
| M 5 | | | | | | | |
| M 9 | - | - | | | | | |
| M 10 | - | - | | | - | - | - |
| M 13 | - | - | - | - | | | - |
| M 18a | - | - | - | - | | | |
| M 19b | - | - | - | - | | | |
| M 20 | - | - | - | - | - | | |
| M 20a | - | - | - | - | - | | |
| M 21 | - | - | - | - | - | | |
| blue area - east | | | | | | | |
| M 6 | | | | - | - | - | - |

To arrange the results in a geographic context, the results are plotted in Figure 9. Upstream sewers with potential for illicit connections are narrowed down and marked as black lines. To date, six hot spots could be identified. In case of the major hot-spot in the sub-catchment upstream of M 10 (south-eastern area), there are not enough measurements yet to refine the hot-spot. 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.

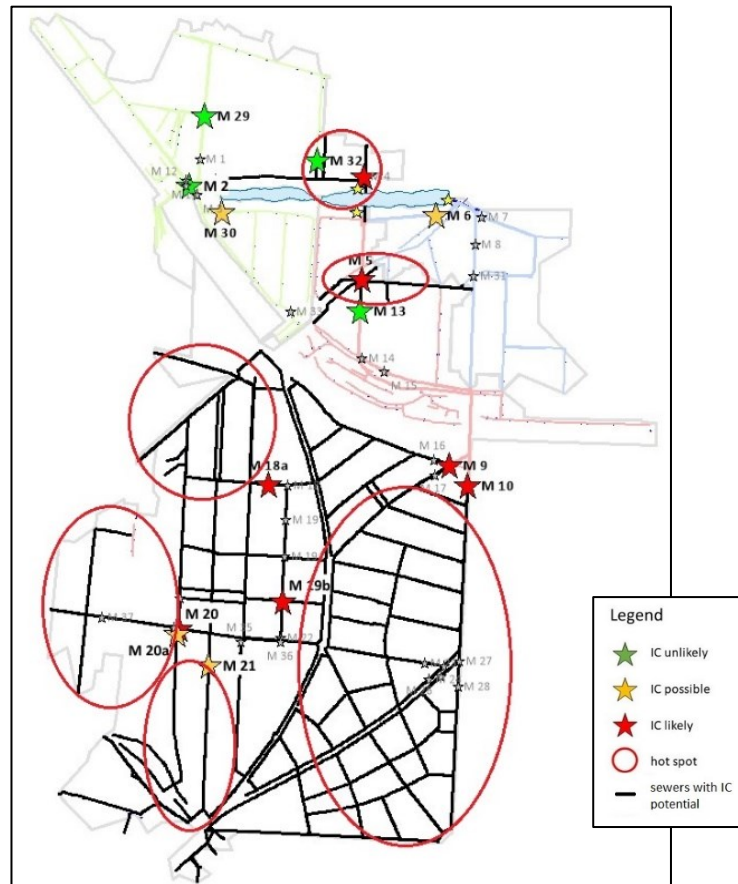


Figure 9: Evaluation of the investigated measuring sites and the interpretation for hot spots.

From a total sewer length of 39 km, DS9 achieved to narrow down a sewer length of 25 km with a strong potential of presence of illicit connections. 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 following equation. Based on the current progress of the investigation and the intermediate data DS 9 is 36% more efficient compared to conventional visual inspections. We could also say that the solution enables to narrow down future investigations to sub-catchments representing 64% of the total network.

$$\text{hotspot screening efficiency} = 1 - \frac{\text{sewer}_{IC,EC}}{\text{sewer}_{IC,VI}} = 1 - \frac{25 \text{ km}}{39 \text{ km}} = 36\%$$

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 an annual basis, staff costs as well as the technical costs for the digital solution and conventional visual inspections will be compared. For the staff cost, a benchmark system will be 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. For the digital solution, the cost of the measuring systems as well as the staff costs for campaign planning, weekly maintenance of the sensors and evaluation of the data must be considered. The KPI will be calculated when the investigation is finished and the whole time needed for the investigation is clear.

$$= \frac{\text{personal costs}_{DS}/\text{year} + \text{technical costs}_{DS}}{\text{personal costs}_{VI}/\text{year}}$$

$$= \frac{\sum (\text{personal time}_{DS} * \text{specific personal costs}) + \sum(\text{sensors})}{\sum(\text{personal time}_{VI} * \text{specific personal costs})}$$

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. 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).

At the present stage of the project it is assumed, that DS9 can be easily transferred to another area or city to investigate illicit connections.

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 10. 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 into the sewer).

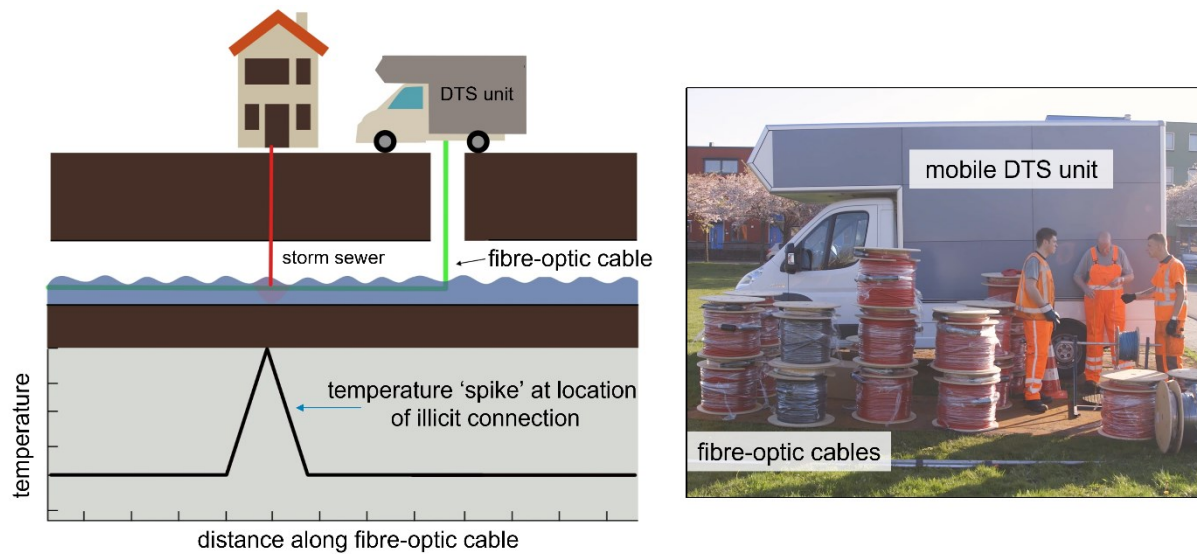


Figure 10: Schematic overview of DTS measurements in a storm sewer (left); example of a mobile DTS unit and several reels with fiber-optic cables prior to installation (right).

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 5 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 9 (left red circle) and Figure 11 (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 11) 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.



Figure 11: 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 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 8. Details on considered input data as well as calculations are given in the subsections below.

Table 8: Overview table of KPI assessment (preliminary results)

| KPI | Short description | Quantification |
|--------------|--|---|
| IC detection | (additional) IC detected by DTS compared to CCTV per km sewer investigated | $\text{additional } IC_{DTS} = \frac{IC_{DTS} - IC_{CCTV}}{\text{length}_{DTS}}$ $\text{additional } IC_{DTS} = \frac{2^1 - 0}{1.5 \text{ km}} = 1.33 \text{ IC/km}$ |
| OPEX ratio | costs of DTS compared to CCTV per km sewer investigated | $\text{OPEX ratio} = \frac{\text{cost}_{DTS}/\text{length}_{DTS}}{\text{cost}_{CCTV}/\text{length}_{CCTV}}$ $\text{OPEX ratio} = \frac{(\text{cost}_{DTS,inst}^2 + 20.000 \text{ €} + 20.000 \text{ €})/1.5 \text{ km}}{\text{cost}_{CCTV}^2/\text{length}_{CCTV}^2}$ |

¹ to be updated after end of monitoring; ² still to be determined

5.3.1 KPI: 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 two illicit connections were discovered (update needed after complete data analysis); with the original CCTV campaign no such connections were found. Over the inspected sewer length of approximately 1.5 km, this yields an additional 1.33 IC per km of sewer length. The background of the results for both methods is describe hereafter.

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 12 (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 09h00 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 12 (right). (NB. Preliminary results, update needed after spatial calibration results.)

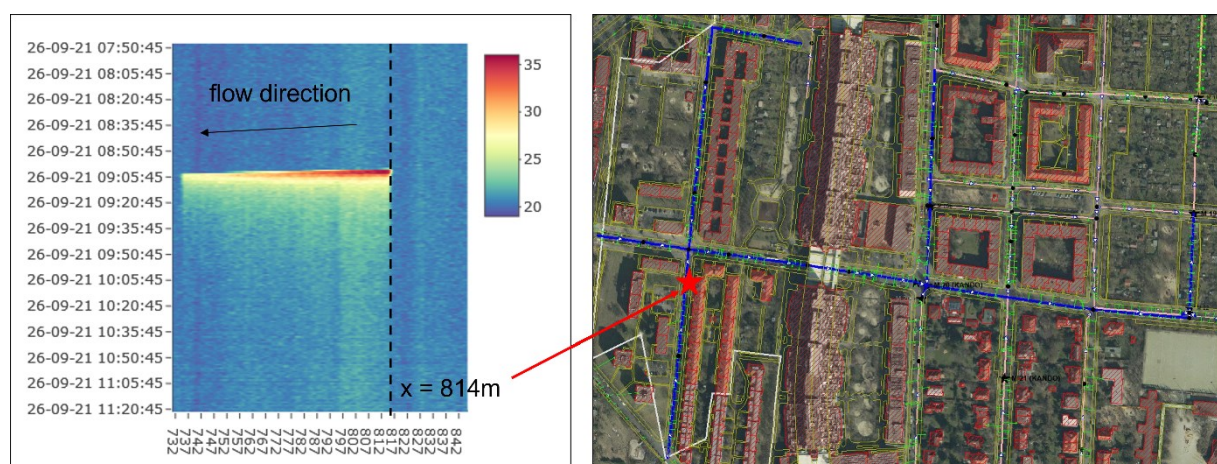


Figure 12: Example of DTS monitoring results (left); corresponding location of the suspected illicit connection (right)

(NB. Overview in table and map of all locations suspected of illicit inflows to be added after completion of the monitoring period - December 2021.)

5.3.2 KPI: OPEX ratio

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

- installation and removal work: [to be defined in final version of D2.2]
- equipment rental: EUR 20.000
- organization, data analysis and reporting: EUR 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: [to be defined in final version of D2.2]

(NB. Considering the costs it should be noted that both methods yield different results associated with these costs, see KPI '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 11, 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 13.

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.



Figure 13: 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.



Figure 1. 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.

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 cost 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 m³/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, 45 CSO points have been selected for monitoring, 36 of them with online sensors and 9 with offline sensors. The monitoring campaign will expand until the end of the project (~ 2 years in total).

In Berlin, DS14 is installed in its biggest combined sewer catchment “Wilmerdorf” 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 m³ 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 m³/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 Wilmerdorf catchment are being monitored, 9 of them with online sensors and 9 with offline sensors. The monitoring campaign will expand 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 9. Details on considered input data as well as calculations are given in the subsections below.

Table 9: Overview table of KPI assessment (preliminary results of the period Sept 2020 -Sept 2021)

| KPI | Short description | Preliminary quantification |
|---|--|--|
| 1. Number of additional CSO events detected | Number of additional CSO events detected since DS14 was applied. | Sofia: ≈290 CSO events from 9 CSO monitored points. Berlin: ≈200 CSO events from 9 monitored CSO points |
| 2. Detection accuracy for CSO frequency | The difference in the number of CSO events detected before and after the DS14 was applied. | Berlin: 8 extra events in RUE20 CSO point corresponding to a 62% of accuracy detection increase. Sofia: Not applicable. No reference available. |
| 3. Detection accuracy for CSO duration | Time of CSO discharging detected before and after the solution was applied | Berlin: 794 min in RUE20 CSO point corresponding to a 65% of accuracy detection increase. |

| KPI | Short description | Preliminary quantification |
|-------------------------------|--|----------------------------|
| | | Not applicable for Sofia. |
| 4. Capex Reduction | Reduction of capital costs related to CSO monitoring | To be calculated |
| 5. Opex Reduction | Reduction of operational costs related to CSO monitoring | To be calculated |
| 6. Increase in model accuracy | Increase in hydraulic model accuracy due to data provided by the CSO sensors | To be calculated |

Context of the results obtained to date: KPI's presented below are calculated based on data obtained during the monitoring period between September 2020 and September 2021. The Covid situation had an important impact on the deployment of the sensors in both case studies. DS14-offline sensors were deployed from September-October of 2020 both in Sofia and Berlin. Unfortunately, online versions were only deployed and operative from August 2021 in Berlin and are still currently being installed in Sofia. Thus, the results for this reporting period are based on data obtained mostly from the DS14 offline sensors. The full set of results will be updated in the final version of D2.2.

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 because very few (Berlin) to none (Sofia) CSO detection instruments were originally in place. Overflow events have been calculated from the temperature data obtained from the sensors and compared with rainfall data for each structure and catchment where the CSO structure is located.

Sofia: Sofia has a total of 232 overflow points and DS14 is planned to be implemented in 45 CSO structures spread in 6 sub-catchments of the city. Results obtained to date correspond to 9 CSO points where around 290 overflow events have been detected since September 2020. Despite the partial number of points monitored to date, information obtained helped already to identify some of the most critical structures in terms of discharge of sewage in Sofia. For instance, CSO points PR15TR2 (Perlovski subcatchment) and PR30LVL (Vladayski subcatchment) contributed to ≈40% of the occurrence detected to date. On the other hand, CSO point PR23TR2 (Perlovski subcatchment) did not overflow anytime despite being exposed to the similar rainfall intensity as PR15TR2 or PR30LVL (≈450mm/year). This information is very important for Sofiyska Voda as they have, for the first time, data about the geographical distribution of overflowing that allows them to start designing adequate actions accordingly.

Berlin: In Berlin, 18 overflow structures of the Wilmersdorf catchment are being monitored, 9 of them with offline sensors and 9 with online sensors. Long term results obtained with the 9 DS14 offline sensors showed around 200 overflow events detected since September 2020. Data from the remaining 9 online sensors is being recorded and will be validated and presented in the final D2.2 report. Similar to Sofia, information collected consists already of a significant increase in the knowledge of the hydraulic behaviour of the catchment. CSO points Rue 23, Rue 20 and Rue Handjery have been identified as the most critical points of the catchment due to the high number of overflow events.

On the other hand, RUE 18 and RUE 19 are the lowest overflowing points with 12 and 14 events respectively since the beginning of the monitoring. The rainfall for the monitored period was ≈394mm.

Calculation of KPI1 at catchment level cannot be performed at that stage until the deployment of online sensors is fully completed and mid-/long-term data including rain events have been recorded and validated.

6.3.2 KPI 2: Detection accuracy for CSO frequency-occurrence

KPI 2 consist of a comparison between the number of CSO events detected before and after DS14 was applied according to the following expression:

$$KPI\ 2 = \frac{\sum \text{number of overflows detected by DS14} / \text{mm rainfall} \cdot \text{time} - \sum \text{number of overflows detected other system} / \text{mm rainfall} \cdot \text{time}}{\sum \text{number of overflows detected other system} / \text{mm rainfall} \cdot \text{time}}$$

KPI 2 values higher than 1 indicate the higher accuracy of DS14 compared to other methods. KPI 2 can be calculated either for a single CSO structure or for a whole catchment.

The relative error between number of CSO events before and after DS14 was also used to calculate the increase in the accuracy detection, according to the equation below:

$$\% \text{ of detection accuracy increase} = \frac{\sum \text{number of CSO detected other system} / \text{mm rainfall} \cdot \text{time} - \sum \text{number of CSO detected by DS14} / \text{mm rainfall} \cdot \text{time}}{\sum \text{number of CSO detected by DS14} / \text{mm rainfall} \cdot \text{time}} \times 100$$

Sofia: KPI 2 cannot be calculated for Sofia as DS14 is the first CSO monitoring equipment deployed in the city, so no reference values are available.

Berlin: On the other hand, in Berlin, the Wilmersdorf sewer system was equipped with commercial water level sensors (external to the project) in 6 locations nearby overflowing structures. Water level sensors measure 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 an example, Figure 2 below presents the CSO occurrence detection in RUE20 from February to July 2021. Rainfall data (red line) shows a very strong correlation with the increase of the water level in the sewer (blue line). According to water level measurements, on five occasions the water reaches the overflow height, fixed at 33m (dashed green line). Results from DS14 in RUE20 (red dots) detected a total of 13 overflow events in the same period. Thus the KPI 2 value for this particular CSO point would be 8 extra CSO detected and the increase in detection accuracy would be of 62%

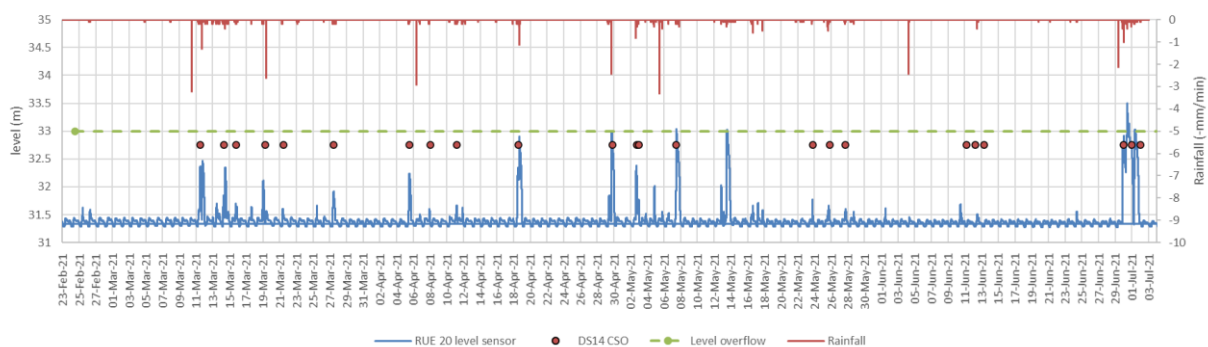


Figure 2. Rainfall, water level and DS14 corresponding to RUE20 CSO point in Berlin.

Historic water level data from Rue20 shows an occurrence of nine overflow events in 2020 and only one overflow in 2019. Pending to have a larger set of data corresponding to all locations of DS14, it seems that DS14 is able to detect a larger number of overflows. Other level sensors are installed in RUE3, RUE4, RUE5 and RUE7 which are equipped with DS14 online versions with limited results yet. Full results of KPI2 will be presented in the final D2.2. report.

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 is calculated according to the following expression:

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

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.

The relative error between duration of CSO events before and after DS14 was also used to calculate the increase in the accuracy detection, according to the equation below:

$$\% \text{ of detection accuracy increase} = \frac{(\sum \text{Time of CSO detected other system/mm rainfall} \cdot \text{time}) - (\sum \text{time of CSO detected by DS14/mm rainfall} \cdot \text{time})}{\sum \text{Time of CSO detected by DS14/mm rainfall} \cdot \text{time}} \times 100$$

Sofia: Similar to above, KPI 3 cannot be calculated for Sofia as DS14 is the first CSO monitoring equipment deployed in the city, so no reference values are available.

Berlin: Over the period between February and July 2021, DS14 estimated the time duration of overflows in RUE20 of 1212 min. On the other hand, the water level sensors only detected 418 min of overflowing in the same period. Thus, the KPI value for this particular CSO point is of 794 minutes, corresponding to an increase of duration accuracy of 65%. Historic water level data from RUE20 showed a duration of 564 minutes in 2020 and only 145 minutes in 2019 which seem to be an especially dry year. Similar to KPI2, DS14 initial data seem to detect longer periods of overflowing compared to water level sensors. However, the full extent of the accuracy of duration will be confirmed with the analysis of the remaining CSO points. KPI3 values for RUE3, RUE4, RUE5, RUE7 and the overall Wilmersdorf catchment will be calculated and reported in the final D.2.2 report.

6.3.4 Other KPI's

Three more KPI's were proposed to quantify the performance and return on investment of DS14. Those are i) KPI4- CAPEX reduction: reduction of capital costs related to CSO monitoring, ii) KPI5-OPEX reduction: reduction of operational costs related to CSO monitoring and iii) KPI6-Increase in model accuracy: increase of hydraulic model accuracy predictions thanks to the data provided by DS14. Quantification of these KPI's is ongoing and will be completed in the next 12 months, in time for the final report.

6.4 Return on experience

Return of experience from city partners point of view: To date, 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 the sensors.

They also mentioned the user-friendly interface of the web platform designed for uploading and 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-malfunctioning of those sensors due to shear and strain produced by wastewater. Also, that increasing the autonomy-battery life of the sensors would be very helpful to reduce the frequency of manhole maintenance activity for operators. The technology providers, ICRA and IoTsens, have already addressed these issues and updated sensors are being sent to both Berlin and Sofia for its testing. SV and BWB also suggested a few modifications in some functions in the monitoring platform, mainly 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 occurrence in a city, which fits in the needs of the water utilities of the project and by extension, many others worldwide. The regular feedback from SV and BWB has been very helpful to expand from the initial concept of DS14, identify its limitations and propose improvements such as connection to rain gauges, communication protocols, etc. The greatest challenge was related to the operational problems with the testing, construction, deployment of the DS14 under pandemic conditions, which has been carried out remotely due to lockdown scenarios. Field teams from SV and BWB have been very helpful in offsetting this limitation but still, a limited operation time of the DS14 impacted the volume of results over the study period. The main challenge for the next months of the project will be to perform an optimal data management of the results generated to ensure a reliable transfer of information to the city partners.

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 odour 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 14 visualises the main components of DS15.

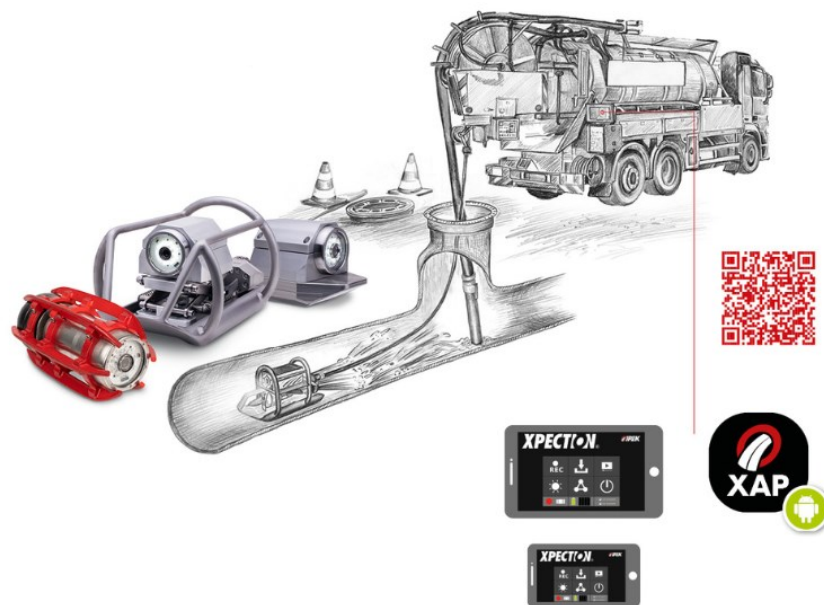


Figure 14: XPECTION device for smart sewer cleaning (DS15) consisting of the cleaning nozzle, the inspection camera and a control panel for visualization.

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 video shots from XPECTION increase the video inspected length of sewer pipes and 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). So far, 2.3 km of the designated 10 km of pipes have been inspected.

In Berlin, the demonstration of DS15 is part of the standard operational routine and includes pipes of the storm, the sanitary and the combined sewer system. 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 current status of the field operations in the demo, already conducted.

Table 10: Overview of the current status of the operations, attended

| | XPection | Current practice |
|------------------------------------|---------------------------|--------------------------|
| Standard cleaning | 29 operations / 44 sewers | to be done |
| Pre-cleaning for CCTV | to be done | 5 operations / 12 sewers |
| Observation of known damages | 24 operations / 25 sewers | 4 operations / 4 sewers |
| Visual control of obstacle removal | to be done | to be done |

In the following months it is planned to complete missing operations in Table 10 to have enough data to compare effort and benefits of DS15 for the different use cases.

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-curricular pipe cross sections, where no other visual technology has been applied. It was found to be a good assistant in finding hidden connections and manholes, in small diameters, where CCTV crawler could not be applied.

For each use case 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 work yard, 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. In the end it is planned to give an overview about effort and benefits with respect to the operational process for each investigated use case.

The benefits of the solution have been assessed via predefined performance indicators (KPIs) (see Table 2). The results are summarised and details on considered input data as well as calculations given in the subsections below.

Table 11: Overview table of KPI assessment (preliminary results)

| KPI | Short description | Quantification |
|--------------------------|--|-------------------|
| 1. Cleaning effort | Time needed for the cleaning steps (mounting the equipment; cleaning; reinstallation) using XPECTION compared to Standard Cleaning | % |
| 2. Inspection efficiency | Related to: 1.1. Observation of known damages 1.2. Finding new damages 1.3. Visual control of obstacle removal | 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) <ul style="list-style-type: none"> • Personal costs • Travel costs | Expenses, € |

7.3.1 KPI 1: Cleaning effort

Table 3: Representation of cleaning effort calculation. Average values (in min) from 29 inspections in Berlin are taken.

| <u>Cleaning steps</u> | <u>Xpection</u> |
|-------------------------------------|-----------------|
| number of operations | 29 |
| preparation time [min] | 15 |
| cleaning time [min] | 39 |
| reinstallation and evaluation [min] | 14 |
| total [min] | 68 |

7.3.2 KPI 2: Inspection efficiency

Table 4: 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 cleaning | Electronic mirror |
|----------------------|----------|-------------------|-------------------|
| number of operations | 36 | 11 | 4 |
| damages found | 42 | 1 | 2 |
| | 117% | 9% | 50% |

7.3.3 KPI 3: Financial value

- CAPEX

Table 5: CAPEX values are rounded values without VAT, taken from Sofia's last delivery contracts. The price of XPECTION is provided from IPEK.

| Equipment | € |
|------------------------------|-----------------|
| Standard nozzle | from 100 to 850 |
| Telescopic camera | 16500 |
| XPECTION | 37800 |
| CCTV (robot camera+ vehicle) | 261000 |

OPEX calculations will be added in the final report

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;
- Visual control of removing obstacles;
- Finding connections and hidden manholes.

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 twice better.

The various cleaning nozzles are stable 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 15: A iPEK XPECTION device for smart sewer cleaning.

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 bypasses⁶ 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 3 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 hours⁷ 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 are shown in Figure 16. The input data arrives from different sources/locations. One or more of the sources are occasionally interrupted, and to produce continuous inflow predictions, 5 different ML models have been trained and deployed to account for missing data instances.

⁶ 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.

⁷ 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.

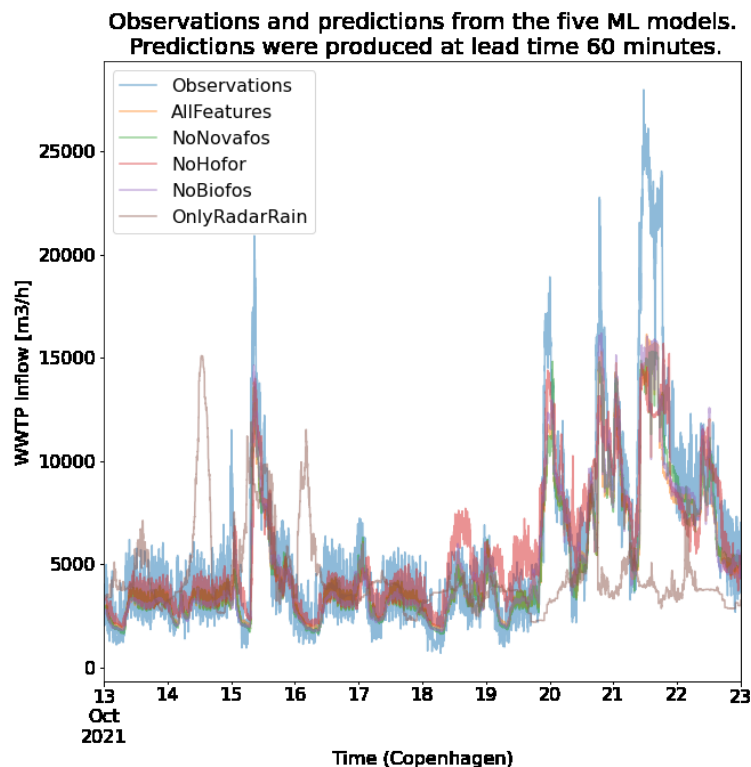


Figure 16: To make the machine learning predictions more robust, five models with different inputs were created. This figure shows observations and predictions from the five different ML models.

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 NWP data. When work was started to put the developed model into production, 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 is expected completed during December 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 17.

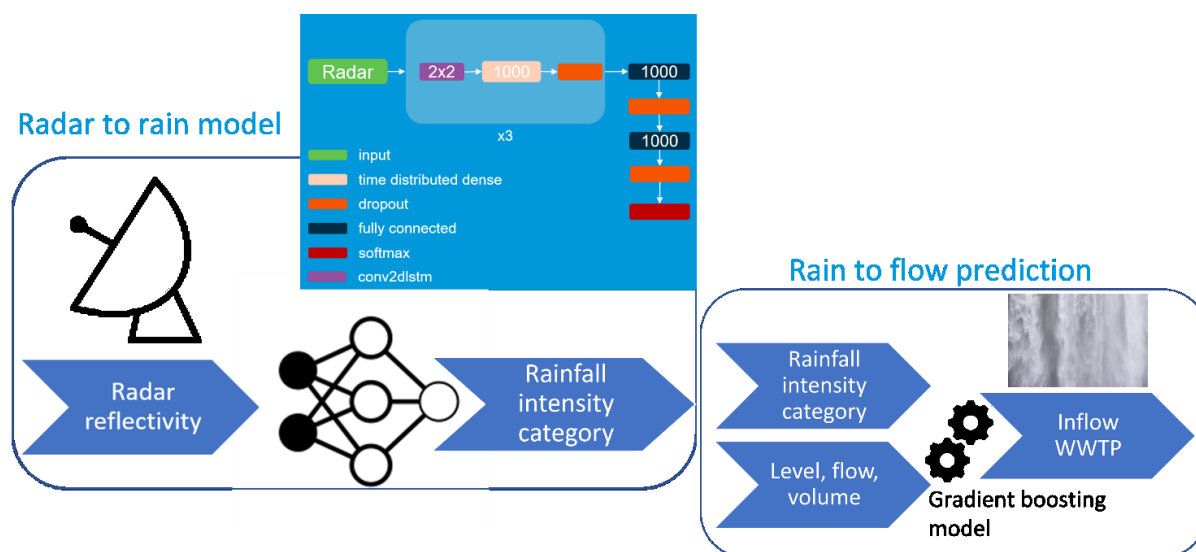


Figure 17: WWTP inflow prediction composite model.

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, observation weights, and optimizers. The architecture settled upon is shown in Figure 17. 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 hyperparameter 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 3 defined performance indicators (KPI). The results are summarised in Table 7. Details on considered input data as well as calculations are given in the subsections below.

Table 12: Overview table of KPI assessment (preliminary results)

| KPI | Short description | Quantification |
|--|---|--|
| Accuracy increase 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 3 hours are considered. | 35-42% for lead times between 30 and 120 min; to be enhanced |
| Accuracy of forecast time for dry weather – 36 h | The KPI evaluates the accuracy of dry weather forecasts for the next 12h, 24h and 36h by comparing forecasts with registered rain data respective to the lead times. | Percent [%] categorized as correct dry weather forecasts |
| Reduction of wrong automatic switching between dry and wet weather operation at the WWTP | The KPI will evaluate 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 [%] reduction-pending. |

8.3.1 KPI 1: Improved forecast during wet weather

The performance / accuracy of the new inflow forecast and the current forecasting system is calculated with regards to observations at the WWTP and the existing inflow forecast “STAR” operational at the WWTP. Performance is evaluated for different forecast times (30, 60, 90 and 120 minutes) via 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.

Preliminary results:

Calculation of averages for ME and RMSE has been made for the periods when the inflow has been above the limit value for ATS (Aeration Tank Settling) Management, BIOFOS wet weather control. The number of negative ME hour values is less than 10% of the calculated values for both STAR forecasts and forecasts from the ML-model. This means that both models underestimate the flow during rain.

For both models, a lower forecast time results in lower ME or RMSE. Forecasts from the ML-model generally have lower error than those from STAR.

Table 13: Mean root mean square error values [L/s] for the STAR model and the new ML model (DS11) for forecast lead times between 30 and 120 min and relative increase in accuracy.

| Lead time | STAR (current practice) | ML Model (DS11) | Accuracy increase |
|-----------|-------------------------|-----------------|-------------------|
| 30 min | 4711 | 3058 | 35% |
| 60 min | 5357 | 3199 | 40% |
| 90 min | 5575 | 3254 | 42% |
| 120 min | 5765 | 3698 | 36% |

8.3.2 KPI 2: Accuracy of forecast time for dry weather – 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.

As mentioned earlier, the implementation of the dry weather forecast is under development, with expected completion date in December 2021.

It is envisaged that rain forecasts are summarized at 3-4 locations within the catchment. For each location, a new forecast is produced on an hourly basis. The forecast will be presented as a table, where minimum and maximum depth are listed for 12h, 24h and 36h ahead. Together with the depth values, the table will also include a confidence value. Separate tables are produced for each location on an hourly basis.

The KPI, will be a comparison of the forecast values and the subsequent rain gauge observations. Details for this KPI is under preparation.

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

The KPI will evaluate whether the new inflow forecast model is 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 with the ML 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 the WWTP exceeding 6,400 m³/h or measured flow at “Dæmningen”, a location upstream the WWTP in the catchment, exceeding 3,000 m³/h once. The ATS is deactivated and dry weather operation resumed when the measured inflow at the plant is ≤ 4,000 m³/h.

Definition of correct start (A):

- A flow forecast activated wet weather operations (ATS- control) and measured inflow exceeds the threshold of 6,400 m³/h during 2 times forecast lead times from the start of a forecast.

Definition of wrong start (B):

- The forecasted flow exceeds the threshold value of 6,400 m³/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):

- Measured inflow activated the wet weather control: The inflow exceeds 6,400 m³/h without wet weather operation (ATS-control) active or the flow at “Dæmningen” exceeded 3,000 m³/h, and the ML did not forecast flows exceeding the threshold value.

Preliminary results on training results:

Data in the tables below are based on data from 01.08.2021 to 26.10.2021. Reservations must be made that it is *not the final version* of the ML- model that will form the basis for the calculations.

The results for the start of ATS-control indicate that fewer rain events are predicted with the ML-model compared to the STAR- model, thereby initiating fewer correct starts (A), however virtually all false starts of rain control are avoided with the ML.

| | A (correct start) | B (wrong start) | C (missing start) |
|-----------------------|-------------------|-----------------|-------------------|
| Existing “STAR” model | 12 | 20 | 34 |
| ML- model | 8 | 1 | 38 |

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/solution, we have developed 5 different ML models, covering the combination of interrupted data source.

Reproducibility and result comparisons for ML models: We use an MLOps platform 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.

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) will address two different control strategies in the network as well as executing the ML model matching in 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. 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, the other an alternative control strategy, which optimizes 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 ¼ h ahead as compared to the 3h forecasts from the ML models, due to technical restraints.

DS12 will be 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 will include a comparison of inflow forecasts and control strategies. Simulated real-time tests will be 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 m³) and thereby reducing bypass at the WWTP, an alternative control strategy is set up in the HIFI-model. 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 basin at inflow rates of 8,000 m³/hour at the plant. The maximum biological capacity at the WWTP is 10,000 m³/hour, which means that all inflow exceeding that threshold bypasses the WWTP and is directly discharged to the river.

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.

NWP (Numerical Weather Prediction) data will be used to illustrate rain probabilities in different locations across the catchment with the aim to understand and leverage the potential of forecast based management of retention capacity in the catchment. Another aim is to make integrated control between WWTP and catchment more dynamic and flexible.

The DSS will be linked to the web platform as part of DS13 in form of illustration of time series of the different forecasts and scenario calculation, rainfall probabilities across the catchment etc.

9.3 Assessment of the digital solution

The benefits of the solution have been assessed via three defined performance indicators (KPI). The results are summarised in Table 14. Details on considered input data as well as calculations are given in the subsections below.

Table 14: Overview table of KPI assessment (to be completed)

| KPI | Short description | Quantification |
|--|---|--|
| Reduction of annual by-pass volume [m ³] | The aim of the KPI is to calculate the relative and absolute reduction of the annual volume of only mechanically treated combined sewage (bypass) at the WWTP discharging into marine waters by comparing the alternative control strategy with current practice. | X % of reduced bypass volume for a defined period: month, demonstration period; m ³ |
| Reduction of nitrogen (N) emissions | 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 for a defined period: month, demonstration period; tons |
| 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. | Money- Euro |

9.3.1 KPI 1: Reduction of annual by-pass volume [m³]

The aim of the KPI is to calculate the reduced amount of bypass- volume with the alternative control scenario in the catchment and AIC (Advanced Integrated Control) between WWTP and the basin.

The KPI is calculated based on simulation results of the HIFI-model on volume stored in the basin during such an event. The saved bypass volume is accumulated and will be calculated as reduced bypass volume for a defined period- month, demonstration period, year etc (to be done). For that, a water balance will be calculated accounting for all inflows and all outflows to the storage pipe plus the difference in bypass volume due to reduced inflow to the plant during a rain event. Like that it can be evaluated whether the alternative scenario is beneficial and does not imply an increase in CSO.

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. Therefore 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 all inflows and all outflows to the storage tunnel plus the difference in bypass volume due to reduced inflow to the plant during a rain event. The calculated water balance is used to calculate the value of the control scenario in terms of reduced CSO.

Reduction of nitrogen emissions are calculated as percent reduction.

$$\% = \frac{(N_{old} - N_{new})}{N_{old}} \times 100$$

Where N = nitrogen

old refers to the baseline simulation

new refers to the alternative control strategy

9.3.3 KPI 3: CAPEX reduction for constructions to reduce bypass

To evaluate whether the alternative control strategy is cost-effective, KPI 3 calculates the investment cost for constructing storage volume at the WWTP equivalent to the obtained effect with the alternative control scenario established and demonstrated in DWC. This is done by using the volume of reduced bypass (scenario output) and translating it into a basin volume at the plant by looking at the rainfall during a given time period. The rain events are linked to a virtual storage volume to obtain the same bypass reduction of TBD m³/year as obtained by the new control strategy. Filling and emptying of a virtual basin for each time step, where filling and emptying is calculated in respect to the biological capacity at the treatment plant, 10,000 m³/time. Results will be illustrated as shown in the example of Figure 18 and volumes will be multiplied with a standard cost of 10,000 kr./m³ to calculate CAPEX savings.

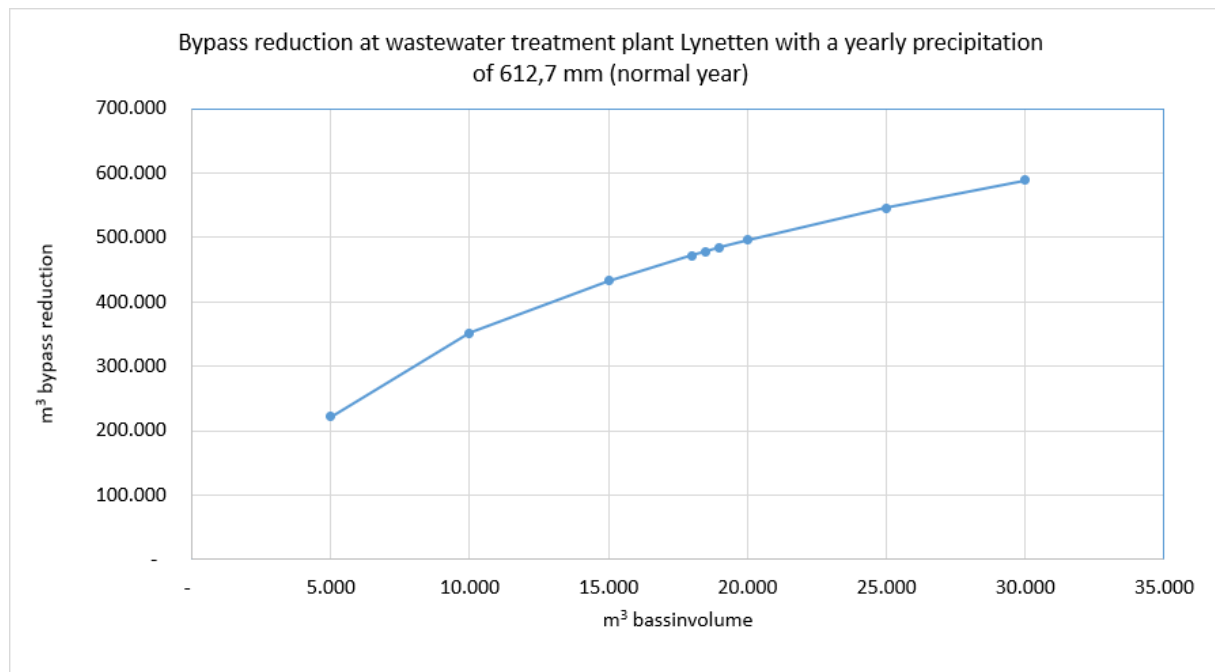


Figure 18: Relationship between bypass reduction and basin volume. For example, to achieve a reduction of 500,000 m³ in bypass you would need a storage basin volume at the WWTP of 20,000 m³.

Model results on overflows are stored in the simulation results file and will be compared to the baseline simulation to evaluate whether the new strategy has a negative impact on overflow volumes and/ or number.

CAPEX calculations will be done on a ½ year basis to evaluate and give a rough estimate on the investment costs to obtain the same effect of reduced bypass as with the new control scenario for the storage volume along the river 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 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 i.e. from late spring/summer in Denmark.

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.

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 will provide a full overview of key data and processes to all involved share- and stakeholders⁸. 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 a 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 19 shows a screen capture of the entry web page, showing all the sensors in the greater Copenhagen. The web app offers further drill down, for visualization of monitored data, inflow predictions and KPI. These visuals are currently being implemented, expected to be ready for use before end of 2021.

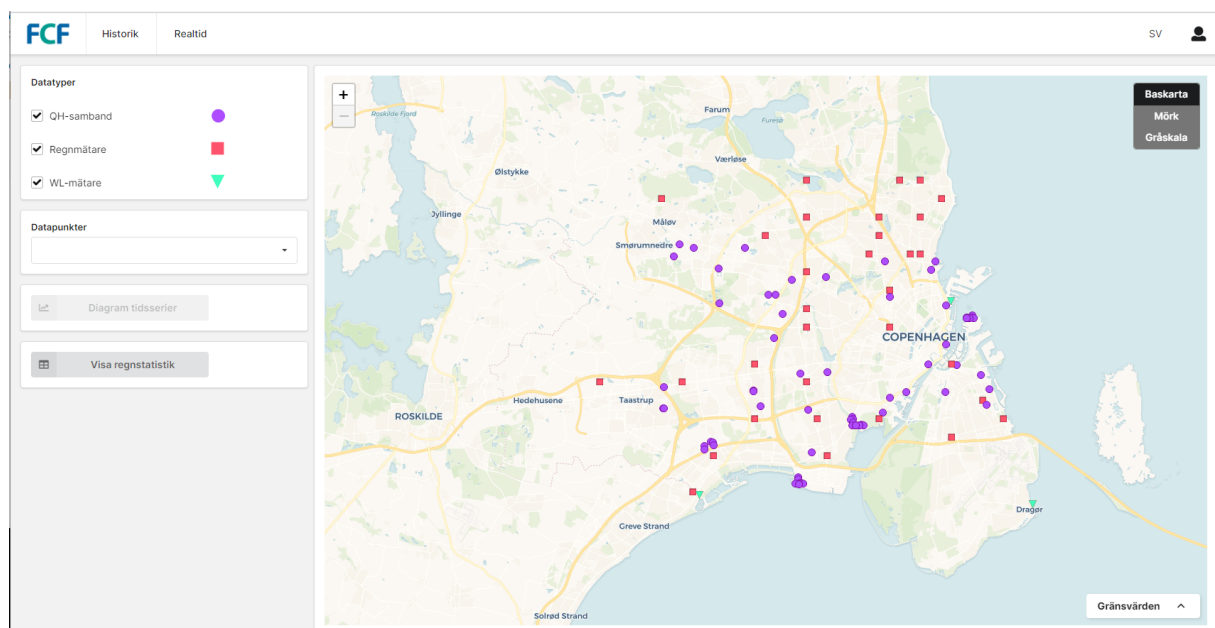


Figure 19: Screen capture of entry page for DS13. Map overview with dynamic links to all sensor stations

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, and includes special features for real-time and long-term planning. FCF offers three different modules:

⁸ Share- and stakeholders are BIOFOS and the 7 utilities in the catchment.

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.

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. Three 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 selected scenario. 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. 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 will also include a separate section for presentations of the KPI's, some of which are calculated in real-time as temporal variables.

An example, from another location, showing a simulated 72 hours forecast, is shown in Figure 20. A similar view will be used to show both the HIFI- and ML forecasts, when the configuration work is completed later in 2021.



Figure 20: Screen capture of a simulated inflow forecast – for a dry weather period. The site is Gothenburg, Sweden, and used as an example only.

10.3 Assessment of the digital solution

The benefits of the solution have been assessed via the defined performance indicators (KPI). The results are summarised in Table 15. Details on considered input data as well as calculations are given in the subsections below.

Table 15: 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. – Pending. At least 2 users will use the system on a daily basis, and at least 50% on a monthly basis. – Pending- expected to be evaluated at the end of the demonstration phase. |
| 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 2022. |
| 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- Done. |

10.3.1 KPI 1: Increased usage, utility buy-in

To increase the usage and utility buy-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 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 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.

KPI quantification pending: There are registered users from 80% of the utilities. 50% of registered users are active every month. – the system is not online yet. There has to be beard in mind that the system is a prototype and that not all of the feedback will be incorporated, only those that lie within the scope of DWC (DS11 and DS12).

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.

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.

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.

Data acquisition: 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. The development team are also considering whether to replace our web application side folder as data source.

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 Altum⁹);
- 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 data* 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 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.

⁹ Micasense Altum - <https://micasense.com/altum/> (last access Nov 2021)

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 is 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 bucket on the Amazon Web Service (AWS) Simple Storage System (S3). Figure 21 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-D2.3 (Technology report).

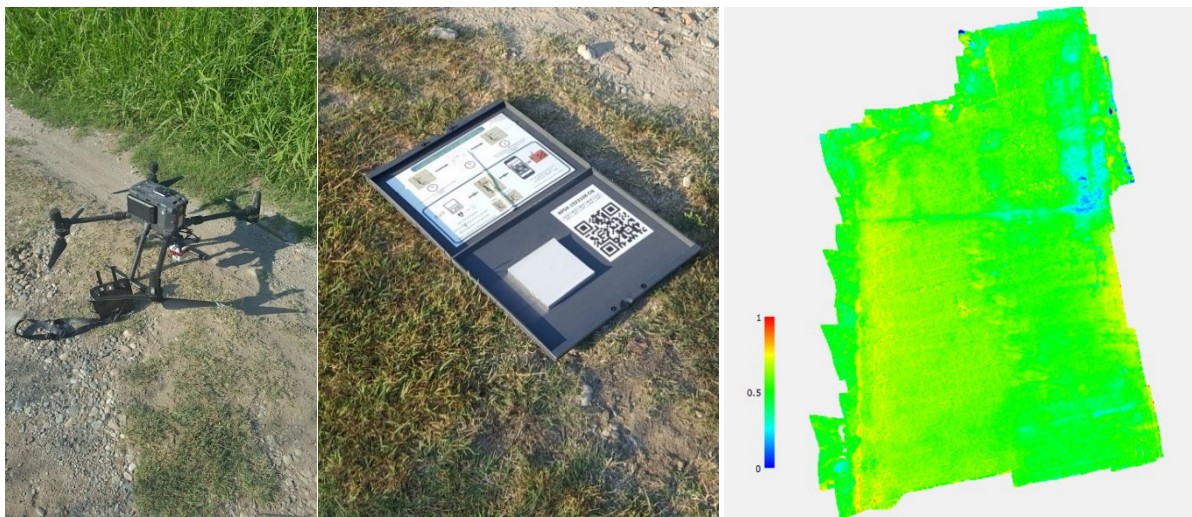


Figure 21: Left: Unmanned Aerial Vehicle on the demo area to detect water stress; center: reflectance calibration target adopted to calibrate data; right: index map that reflects the crop status according to the Normalized Difference Red Edge (NDRE) Index – 5th August 2021

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 products¹⁰. L2A images were processed using the Application Programming Interfaces (APIs) provided by the SentinelHub service¹¹ 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&Drop¹²].
- 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 $[t_0 - T, t_0]$ where t_0 refers to the acquisition time of the satellite / drone. In addition, a weather station [ATMOS41, METER ENV.¹³] was installed near the demo 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 22 shows the demo site and main related components.

¹⁰ Sentinel-2 Product Specifications <https://sentinel.esa.int/documents/247904/685211/Sentinel-2-Products-Specification-Document> (last access Nov 2021)

¹¹ SentinelHub API - <https://www.sentinel-hub.com/develop/api/> (last access Nov 2021)

¹² Sentek Drill & Drop - <https://sentektechnologies.com/product-range/soil-data-probes/drill-drop/> (last access Nov 2021)

¹³ Meter Environment ATMOS 41 <https://www.metergroup.com/environment/products/atmos-41-weather-station/> (last access Nov 2021)

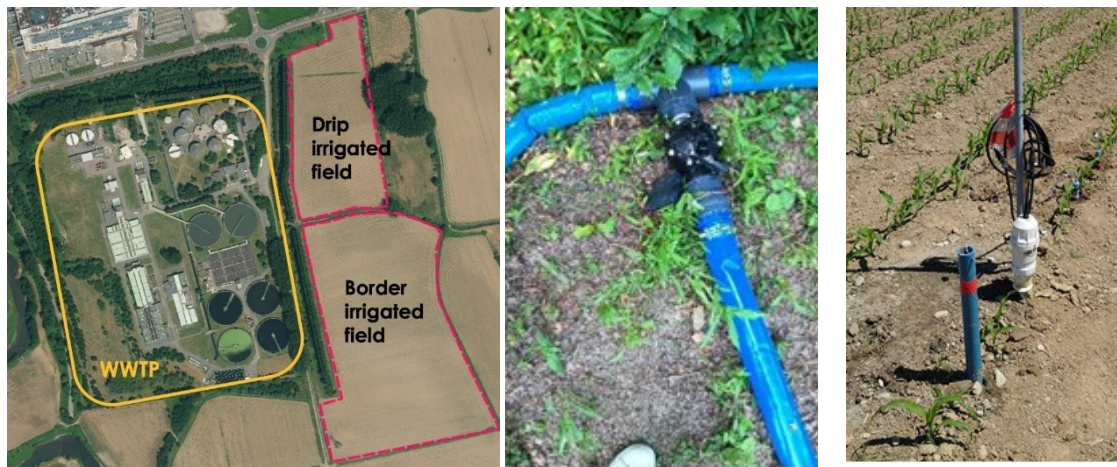


Figure 22: Overview of demo site (left), drip irrigation system installation (center), piezometer, water content probe + GSM modem, porous cups (right).

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.

11.3 Assessment of the digital solution

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

Table 16: Overview table of KPI assessment (preliminary results)

| 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. |

Figure 23 shows how the *Seasonal Local Water Stress* changes over the reference period. 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.

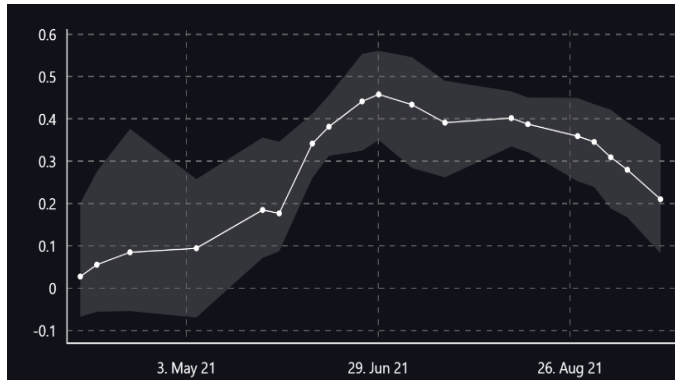


Figure 23: Evaluation of the index (NDMI) over a 6-month time span (last point is 23 Sept 2021); white curve represents the average value inside the demo site while the gray area shows the 10th and 90th percentiles

The raster (stress) map (Figure 24, 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 24, 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.).



Figure 24: Left: evaluation of the SLWS (20th Jul 2021); green pixels are related to areas with lower stress; purple refers to areas with higher stress. Right: evaluation of the SLNS (20th Jul 2021); green-orange pixels are related to areas with lower stress; dark orange /purple refers to areas with higher stress

Figure 25 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 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).

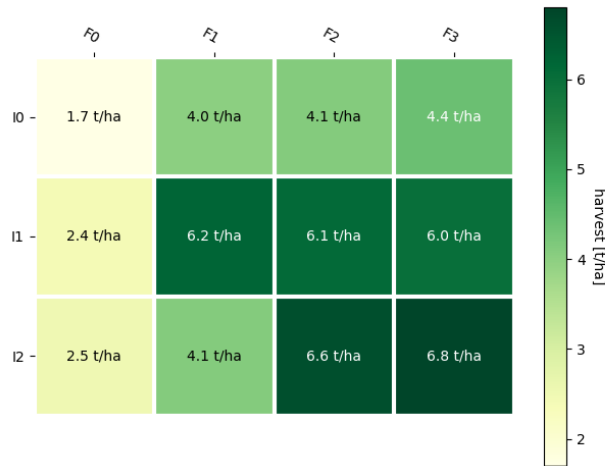


Figure 25: Effect of water and irrigation stress on the final yield. I0, I1 and I2 and F0, F1, F2 and F3 are levels of irrigation (0, 50 and 100% of evapotranspiration) and fertilization, mainly Nitrogen, (0, 65, 225 and 340 and kg/ha) respectively.

11.3.1 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) to invert the logics. 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

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).

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. $index_t$ 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)^{14, 15}. 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 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:

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

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 of 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.

¹⁴ 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>

¹⁵ 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>

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).

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) represent 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.

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

12.1 Digital solution

Currently, in many regions, treated wastewater is often discharged into existing open-channel agricultural networks and provided to 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 wastewater 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.



Figure 26: UI of the MMT – farmer view

The Match Making Tool interacts with the end-user with a reduced and user-friendly interaction. 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 geodatabase 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, reel, drip, ...)
 - Farmers could also provide dynamic data such as the crop development stage; this would allow for a more accurate estimation of irrigation needs.

These data are pre-processed using the Soil Water Atmosphere Plant (SWAP) software¹⁶, 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 wastewater is available for reuse and its related water class in real time. Figure 26 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 27); 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 be obliged to follow the irrigation advice provided by the MMT).

Farmers could benefit from the use of this tool also without treated wastewater 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).

¹⁶ Soil Water Atmosphere Plant (SWAP) - <https://www.swap.alterra.nl/> (last access Nov . 2021)

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 wastewater 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.

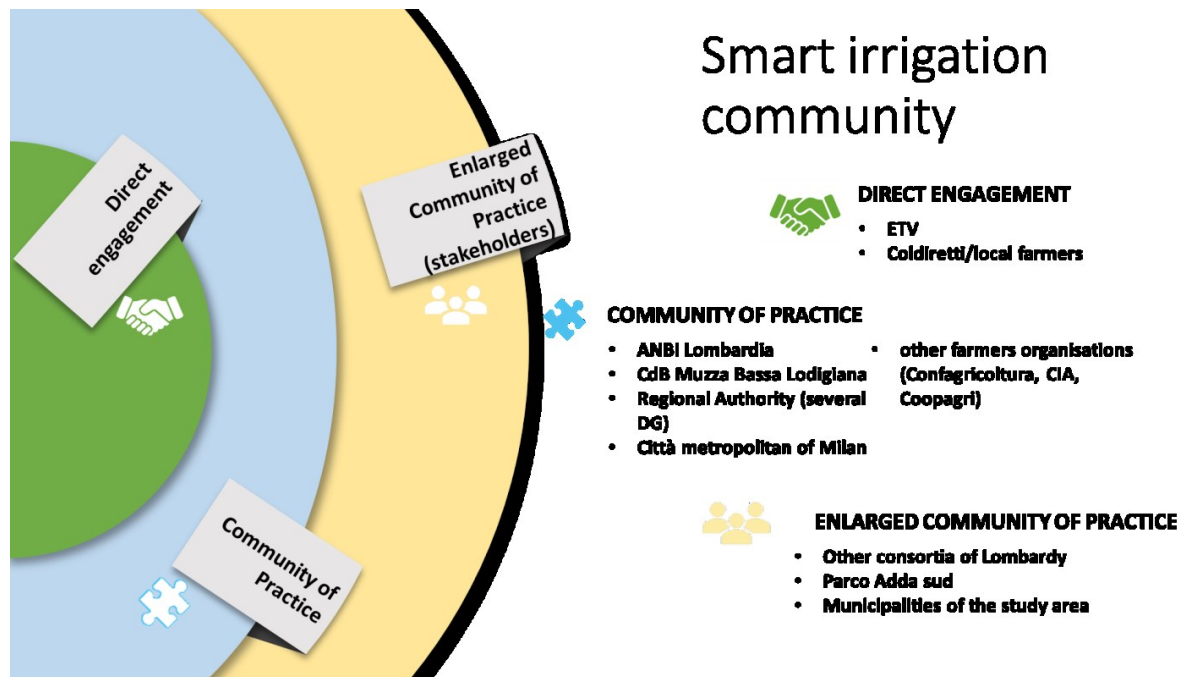


Figure 27: Smart Irrigation Community that is involved in the MMT

12.3 Assessment of the digital solution

The benefits of the digital solution were assessed via three performance indicators (KPIs; Table 17) which represent the water, fertilizer and CO₂ savings offered by two scenarios that use treated wastewater 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 from an open channel for a fixed time and interval (typical scenario adopted by farmers), using a pump powered by a tractor and water from a natural river (Figure 28).
- 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).



Figure 28: border irrigation (left) vs. drip irrigation (right) at Peschiera Borromeo.

Table 17: Overview table of KPI assessment for DS5.2 (preliminary results)

| 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. | <ul style="list-style-type: none"> 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 wastewater 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). | <p>PRELIMINARY ESTIMATES:</p> <ul style="list-style-type: none"> S1: 48% of saved fertilizer compared to the baseline (37 kg/ha) S2: 104% 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. | <p>PRELIMINARY ESTIMATES:</p> <ul style="list-style-type: none"> 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:

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 (S_0) and that provided through drip irrigation (S_x , where x can be either scenario 1 or 2):

$$ASW = V_{S_0} - V_{S_x}$$

Where:

V_{S_0} is the yearly volume (mm) provided through border irrigation (S_0) 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_{S_x} is the yearly volume (mm) provided by pump in scenarios S_1 and S_2 , 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.

Preliminary 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 (S_0) and scenarios S_1 and S_2 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 (NFW_{S_x}) and the amount that needs to be provided using standard fertilizers over the season (NFF) using a standard rate for corn:

$$RSF = \frac{NFW_{S_x}}{NFF} * 100 \quad (\%)$$

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:

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

Where:

NFF is the amount of nitrogen provided within the baseline scenario (S_0) through top-dressing¹⁷ over the season (kg/year).

NFW_{Sx} is the amount of nitrogen provided through the treated wastewater within scenarios S_1 and S_2 over the season (kg/year).

Preliminary results of provided N amounts to the field for the first season:

- **Baseline:** 70 kg/ha as top-dressing
- **S1:** 34 kg/ha from treated wastewater
- **S2:** 74 kg/ha from treated wastewater

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 CO₂ produced within the baseline scenario (S_0) comes from:

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

The CO₂ produced within the drip irrigation scenarios (S_1 and S_2) 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_{CO_2}), can be calculated as the difference between the CO₂ produced under the baseline scenario (S_0) and the re-used water scenarios (S_1 and S_2):

$$S_{CO_2} = CO_{2S_0} - CO_{2S_x} \quad (\text{kg/year})$$

Where:

CO_{2S_0} 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 CO₂ produced for fuel unit, the amount of CO₂ produced for nitrogen unit;

CO_{2S_x} 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 CO₂ produced per unit of energy consumed, and the CO₂ emitted per unit of nitrogen produced in case that provided through fertigation is not enough.

¹⁷ The top-dressing amount is provided once and must consider nitrogen loss due leaching and denitrification processes.

Preliminary results of produced CO₂ for the first season:

- **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 can be further refined by considering 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 BBCH¹⁸);
- meteorological conditions;
- 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. Although this aspect could be mitigated by using 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 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 FIWARE¹⁹, gained flexibility and robustness and can now manage the integration of data that come from the WWTP effectively.

¹⁸ BBCH, <https://www.politicheagricole.it/flex/AppData/WebLive/Agrometeo/MIEPFY800/BBCHengl2001.pdf> (last access Nov 2021)

¹⁹ FIWARE - <https://www.fiware.org/> (last access Nov 2021)

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 wants to provide suggestions to end-users that -if considered- will enable a better management of water resources.

13 Final remarks and outlook

The presented report gives a first assessment of the different digital solutions of DWC-WP2. For most solutions the assessment is only preliminary, as not all required data have been collected yet. In the following twelve project months the demonstration projects will continue, more data will be collected and the quantification of the key performance indicators will be refined. An updated version of this report will be published in Nov. 2022. However, the presented results already reveal a high potential of the digital solutions to improve urban water management.



Leading urban water management to its digital future

digital-water.city
 **digitalwater_eu**



digital-water.city has received funding from the European Union's H2020 Research and Innovation Programme under Grant Agreement No. 820954.