Article:

Gleeson, K. orcid.org/0000-0002-3767-3001, Husband, S. orcid.org/0000-0002-2771-1166 and Boxall, J. orcid.org/0000-0002-4681-6895 (2025) Multi-parameter multi-sensor data fusion for drinking water distribution system water quality management. AQUA — Water Infrastructure, Ecosystems and Society. jws2025002. ISSN 2709-8028

https://doi.org/10.2166/aqua.2025.002

corrected Proof

AQUA

Water Infrastructure, Ecosystems and Society

 AQUA — Water Infrastructure, Ecosystems and Society Vol 00 No 0, 1 doi: 10.2166/aqua.2025.002

Multi-parameter multi-sensor data fusion for drinking water distribution system water quality management

Killian Gleeson *, Stewart Husband and Joby Boxall

The School of Mechanical, Aerospace and Civil Engineering, The University of Sheffield, Sheffield S10 2TN, United Kingdom

*Corresponding author. E-mail: k.gleeson@sheffield.ac.uk

KG, 0000-0002-3767-3001; SH, 0000-0002-2771-1166; JB, 0000-0002-4681-6895

ABSTRACT

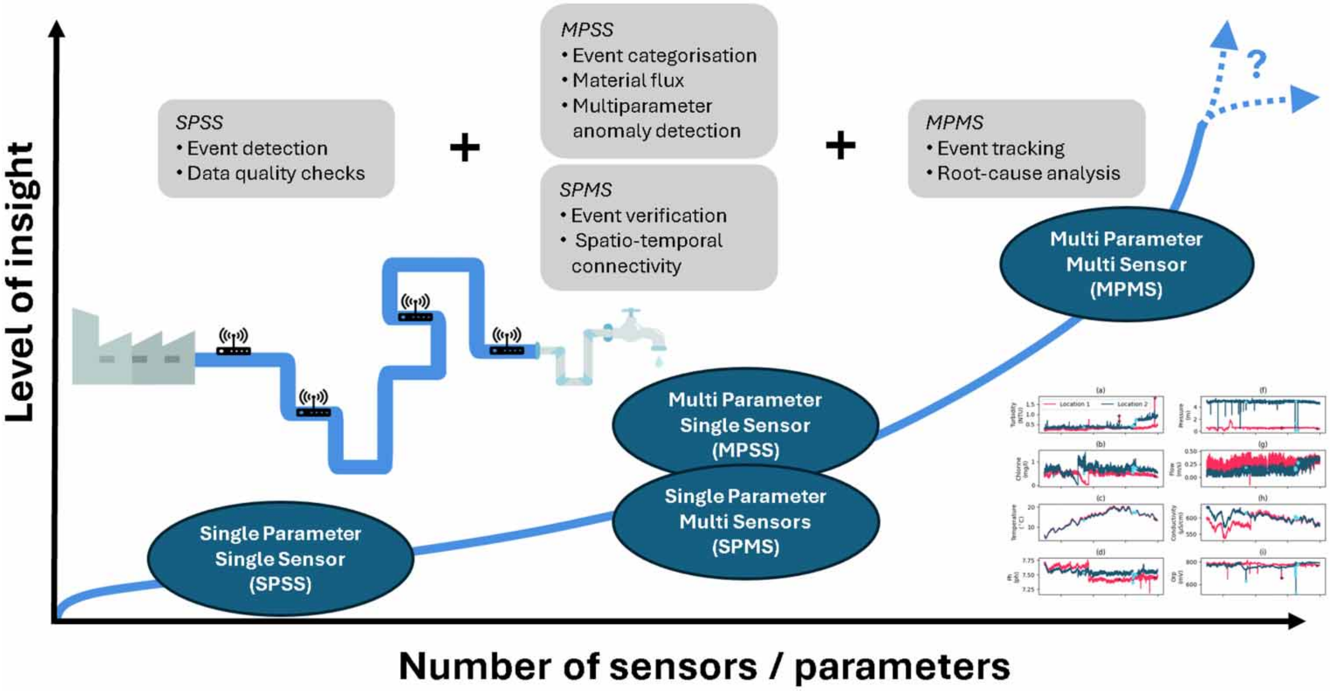
Water quality events within drinking water distribution systems are commonly first detected by consumers. This undermines confidence, is in contrast to the level of service consumers now expect and in extreme cases can indicate a risk to public health. The objective of this paper is to propose and show how the value and insight gained increases in progression from single parameter, single location to multiple parameter multiple location sensor approaches. This is done using real-world datasets from operational systems and application of multiple analytical approaches in combination to extract actionable insights. Analytical methods include: cross-correlation for system connectivity and transit time derivation; an innovative turbidity event scale system; and material flux analysis of discolouration material. This research demonstrates the ability to confirm and track network-wide events, determine root causes, and inform proactive management via advisory event scores. The evidence provided of the multiplicative jumps in value in progressing towards multiple parameter multiple sensor approaches is vital to help guide future strategies for networks of water quality sensing.

Key words: data fusion, drinking water distribution systems, drinking water quality, event detection, time series, water quality

HIGHLIGHTS

- Multi-parameter multi-sensor fusion yields multiplicative increase in water quality insights.
- Novel application of combined analytics demonstrated on real drinking water networks.
- Operational datasets made openly available for future water quality monitoring research.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Ensuring the delivery of wholesome drinking water to consumers is a critical public health responsibility. Drinking water is treated to meet rigorous international standards (EU 1998; WHO 2017; DWI 2018; USEPA 2018) but its delivery through vast, buried and aging drinking water distribution system (DWDS) infrastructure comes with water quality risks that are poorly detected and understood. Monitoring of DWDS rarely extends beyond regulatory compliance via minimal random daytime sampling. This provides incredibly sparse (temporally and spatially) snapshots into these complex, dynamic systems. Water service providers (WSPs) are often only made aware of water quality events retrospectively through customer complaints (Cook *et al.* 2016; Boxall *et al.* 2023). In the UK, discoloured water is the primary water quality issue (DWI 2023). Pressure from regulation and customer expectations to reduce customer contacts for discolouration are driving some innovation projects to explore the deployment of continuous water quality sensors within DWDS. However, the value of the resulting time series data has yet to be realised, with much simply assessed through manual visual interpretation (Gleeson *et al.* 2024). As urban population growth and climate change puts increased strain on DWDS (UN-INWEH 2020), there is a need to develop data-driven approaches to improve management of these vital assets and ensure the safe delivery of drinking water.

Deploying continuous water quality monitors within DWDS comes with numerous challenges and choices: selecting parameters; finding monitoring locations; determining monitor density; instrument maintenance needs; accuracy and confidence in data quality. Many of these are compounded by the use of technologies that are typically sensitive analytical instruments deployed in harsh remote environments. The nature of the dataset obtained directly impacts what analysis approaches are possible and what network insights can be derived. The ultimate goal is to utilise a deployment strategy that can best inform the actionable insight desired. However, to achieve this we must understand what insights can be obtained from what data and how this changes as a function of the deployment strategy. Central to this is understanding how the level of obtainable insight changes with more sensor locations and parameters.

Two commonly identified parameters of interest with potential to inform insight are turbidity and chlorine. Turbidity, an optical measure of water clarity, is important for measuring discolouration that is the primary consumer observed water quality issue (Boxall & Saul 2005). Change in disinfection residual can provide information about reactions and interactions occurring within DWDS and even external contamination, as chlorine responds and reacts with various substances

(Murray & Haxton 2010). Monitoring chlorine, or turbidity, without any other parameters or sensor locations may therefore in some cases be a sole objective. Recent work reviewing discolouration monitoring developed a turbidity event scale that distinguishes between reactive alarm (>4 NTU) and alert (2–4 NTU) events, as well as providing proactive advisory warning scores based on crowd-sourced labelled data (Gleeson *et al.* 2024). This demonstrates that actionable insight can be obtained from individual parameter time series data sets, in this case informing the management of discolouration risk.

The increased value of monitoring at more than one connected location within a DWDS has been reported. For example, comparison of chlorine time series profiles at different sensing locations has been shown to yield useful connectivity and transit time information (Gleeson *et al.* 2023b). Turbidity and chlorine are prone to data quality issues and a data quality framework has been developed to assess the performance of these sensors when installed in DWDS (Gleeson *et al.* 2023a). This framework can aide proactive sensor maintenance, as well as filter datasets for subsequent analysis. A key feature of the framework is a third stage which uses cross comparison with other confirmed-connected sensor locations demonstrating value in combining different sensor locations. Kennedy *et al.* (2024) showed how combining turbidity sensor locations, in this case at the inlet and outlet of service reservoirs, can reveal sink or source material behaviour and inform proactive cleaning interventions. The ability to combine sensor locations depends on the spatial deployment density with both temporal and spatial monitoring density a trade-off between cost and value. 15-minute sampling is common and provides good definition of daily patterns (Mounce *et al.* 2012), whilst 1-minute intervals can offer benefits for capturing DWDS dynamics (Gaffney & Boult 2012). Instrumentation capable of delivering water quality data sub 1 s is not currently available, but combining it with 100 Hz+ pressure data to understand the water quality interactions with hydraulic transients has been shown (Aisopou *et al.* 2012; Weston *et al.* 2021). Spatial density depends on objectives and suitable locations, but collecting a dataset with multiple connected sensors means that any subsequent analysis will have a higher confidence.

Similar to the benefits of combining sensor locations, combining different parameters from the same location has been shown to improve overall analytical processes in other fields, specifically it is common to utilise combinations to detect anomalous data. Principal component anlysis (PCA) is a dimensionality reduction technique that has been found to be an effective way to reduce highly correlated high-dimensional datasets into smaller uncorrelated datasets more suited to unsupervised anomaly detection (Dunia *et al.* 1996; Aggarwal 2016). Isolation forests (Liu *et al.* 2008), elliptical envelopes (Rousseeuw & Driessen 1999) and local outlier factor (LOF) (Breunig *et al.* 2000) are popular unsupervised anomaly detection methods that look to create a boundary between normal and abnormal datapoints. One-class support vector machines (OCSVM) is an unsupervised variant of the popular supervised classification method support vector machines (SVM) that splits data into two classes (Shin *et al.* 2005). When it comes to water quality sensors, it has been shown that combining them with hydraulic parameters like flow and pressure are also relevant, for example hydraulic changes impacting head loss and shear stress can initiate discolouration that is measurable with turbidity (Husband *et al.* 2008). When flow and turbidity are multiplied together, material flux can be estimated, allowing the transport of discolouration material to be quantified (Gaffney & Boult 2012; Furnass 2015).

Previous research has hence demonstrated the increase in value when combining the same parameter at different sensing locations, as well as when combining different parameters at the same location.

2. METHOD

This paper proposes that progressing towards multiple parameters and multiple sensors (MPMSs) strategies in combination with appropriate analytical methods will yield a multiplicative increase in actionable insight, and to demonstrate this for data from operational DWDS. In theory, one might expect the value to increase multiplicatively due to the increased confidence and analytical options. The term multiplicative in this context refers to the increase value being greater than simply adding together the individual value from each single sensor and parameter. This would be an important finding due to its potential impact on cost-benefit analysis when deriving a deployment strategy.

This research explores how MPMS datasets, taken from operational DWDS, can be combined and transformed into actionable insights to safeguard drinking water quality. By using real-world data, this research addresses a common deficiency in DWDS water quality event research where synthetic events are introduced to modelled derived data before developing detection etc. approaches (Murray & Haxton 2010; Perelman *et al.* 2012; Li *et al.* 2019; Muharemi *et al.* 2019). In examining MPMS datasets, this research investigates the nature of the presumed increase in level of value derivable when combining sensor locations and parameters. To support reproducibility and enable further research in this area, the datasets used in this study are made freely available, with the exception of one case study where commercial restrictions apply (https://doi.org/10.15131/shef.data.28045628.v1).

To investigate the potential of sensor networks in DWDS to provide insight to help protect water quality four existing datasets provided by different UK WSP were examined. A crucial element in water quality monitoring is how many sensors and parameters to monitor. It is often assumed that more sensors and parameters equals more insight but this relationship has yet to be robustly examined. Therefore the aim of this research is to investigate whether a proposed increase in insight obtainable is seen as analytics move from single parameter single sensor (SPSS) to MPMSs. The deployment strategy of the datasets used herein was not defined by the research, it was a function of other purposes and thinking within each water company. Our selection criteria was datasets that would enable a research methodology that investigated the impact in moving from SPSS analytics, passing via multi-parameter single sensor (MPSS) or single parameter multi-sensor (SPMS) stages to ultimately MPMS analytics. All available data was used in each case study, with the analytical approach selected to meet the needs of each dataset. The approach here focused on information that could be extracted from water quality monitor data alone, a benefit being this is achievable without necessarily requiring additional network data and information. Analytical methods that can be applied vary across this progression and this section reviews the possibilities available at each stage.

2.1. Single parameter single sensor

When analysing a SPSS water quality time series dataset from a DWDS it is crucial to consider uncertainty, particularly in differentiating sensing errors from events. While the data quality assessment framework illustrated in Figure 1 (Gleeson *et al.* 2023a) can only be partially applied for SPSS, conducting Stage 1 is an essential first step to assess the sensor performance and determine what data is suitable for further analytics. Preprocessing steps, such as removing drift and single-point outliers, may be necessary depending on the subsequent analysis requirements. Some approaches do not rely on absolute value accuracies, circumventing calibration challenges at low turbidity levels. Examples of this include the event scale method of Gleeson *et al.* (2024) or the daily standard deviation of turbidity (Mounce *et al.* 2015), which captures how much discolouration material is mobilising due to diurnal flow patterns informing the potential for discolouration without absolute value dependencies.

2.2. Multi-parameter single sensor

With multiple parameters at the same location, analysis confidence theoretically increases. Sensor faults are more easily detected, as they may be apparent in multiple parameters. Different analytical approaches combining parameters become applicable, enhancing insights obtainable. An example is multiplying turbidity and flow to generate material flux (NTU·m^3/hr) (Furnass 2015). This can be integrated to calculate total material quantities, enabling precise discolouration material quantification rather than just discolouration material concentration, which is effectively what turbidity provides. Material flux can also be converted to particulate mass if the turbidity-suspended solids relationship is known (Gaffney & Boult 2012). With increased parameters, dimensionality reduction techniques such as principal component analysis (PCA) combined with unsupervised anomaly detection can automatically identify anomalous features across variables (Dunia *et al.* 1996; Aggarwal 2016).

2.3. Single parameter multi-sensor

SPMS datasets allow for water quality data to be compared across locations, enabling higher confidence analysis, for example, knowing which locations are hydraulically connected. Cross-correlation has proven effective in determining hydraulic connectivity between chlorine sensors and estimating transit times between sensing locations (Gleeson *et al.* 2023a). However, this method does not work equally well with all parameters, with chlorine for example showing more suitability

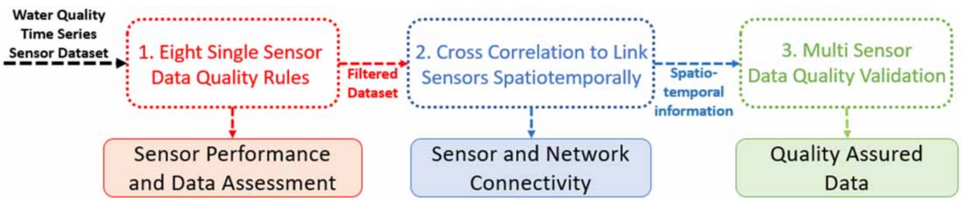


Figure 1 | Three-stage data quality assessment framework (simplified from Gleeson *et al.* 2023b).

than turbidity. Having two or more confirmed-connected sensing locations enables quality comparisons as water passes through complex networks, potentially allowing for root-cause estimation and downstream risk evaluation during water quality events.

2.4. Multi-parameter multi-sensor

MPMS analytics combine the benefits of MPSS and SPMS, theoretically leading to a more complete and confident assessment. Analytics suited to MPSS, such as material flux, can be compared across connected locations, allowing for material tracking in the case of discolouration events.

3. RESULTS

To explore the benefits of MPMS water quality monitoring, four case studies featuring different combinations of parameters and numbers of sensors are examined. These are summarised in Table 1. The case studies range from SPMS to MPMS with the increase in value obtained compared to what would be possible with SPSS monitoring presented. The first two case studies both focus on the benefits of MPMS analysis of discolouration events. The final two case studies look at increasing sensor density, with case study 3 focusing on 6 sensors deployed along the same main, and number of available parameters, with the final case study focusing on sensors deployed measuring eight different parameters.

3.1. Case study 1 – Combining sensors and parameters for MPMS analysis of alarm turbidity event

This case study combines free chlorine, turbidity and flow at two locations, as shown in the simple schematic in Figure 2, in order to analyse a discolouration event. Before the MPMS analysis, it is important to consider what the SPSS analysis would have looked like. A single chlorine (Figure 3(a)) or flow time series (Figure 4(b)) would not indicate anything had occurred. A turbidity 'alarm' (Gleeson *et al.* 2024) event would have been detected in either turbidity time series (Figure 4(a)) but would have been of low confidence: it may have been a sensor error or simply a localised event. By combining the available data, the level of insight obtained and confidence increases; in the first instance that both turbidity time series show an alarm event suggesting it is not sensor error, if they are connected. Figure 2 shows how cross-correlation (Gleeson *et al.* 2023b) of the

Table 1 | Summary of case studies presented

Case study	Summary	Parameters/locations/additional data	Analytic techniques
1	Combining sensors and parameters for MPMS analysis of alarm turbidity event	Chlorine, Turbidity, Flow/×2 locations/none	Data quality assessment, Turbidity drift detection and correction, Cross-correlation, Material flux, Daily peak flow rate, Turbidity event scale
2	MPMS alarm event following mains flow increase with associated customer contacts	Chlorine, Turbidity, Flow/×3 locations/mains flow, customer contacts	Data quality assessment, Cross-correlation, Daily peak flow rate, Material flux, Turbidity event scale, Contacts Analysis
3	SPMS analysis of six turbidity sensors in single main	Turbidity/×6 locations/Mains flow	Median daily standard deviation, Turbidity event scale, Material flux (using only available mains flow rate)
4	MPMS dimensionality reduction and anomaly detection	Turbidity, Chlorine, Temperature, pH, Pressure, Flow, Conductivity, ORP/×2 locations	Dimensionality reduction (PCA), Unsupervised anomaly detection (IF, EE, LOF, OCSVM)

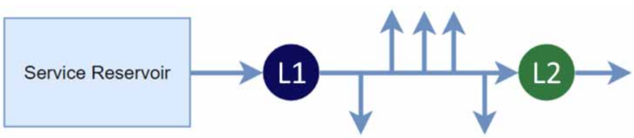


Figure 2 | Simplified network schematic showing sensors at locations 1 and 2.

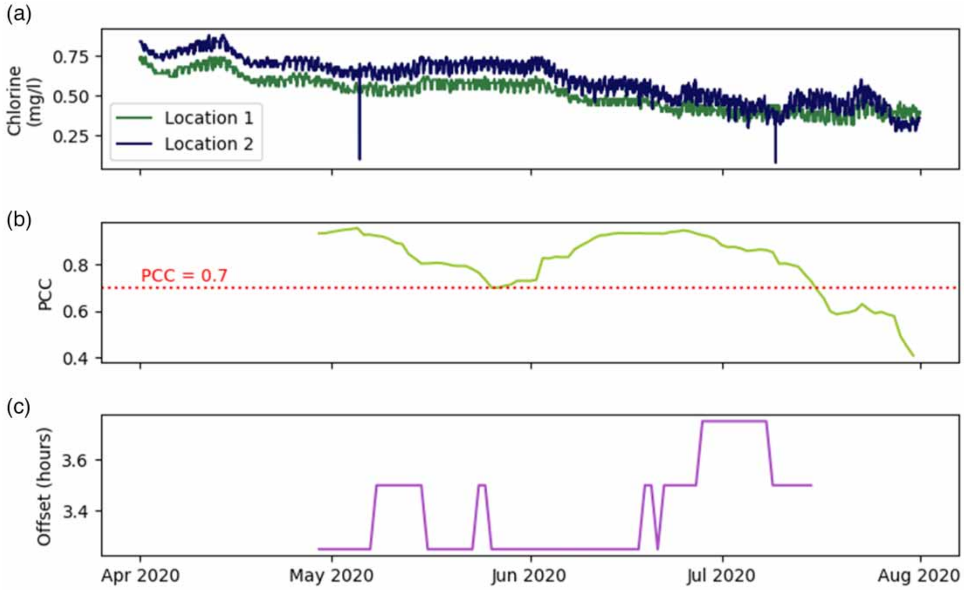


Figure 3 | Sliding cross-correlation is used to derive transit times between two chlorine sensors. Chlorine time series at locations 1 and 2 (a), maximum sliding cross-correlation coefficient for a 4-week window (b), and corresponding sliding offset (c).

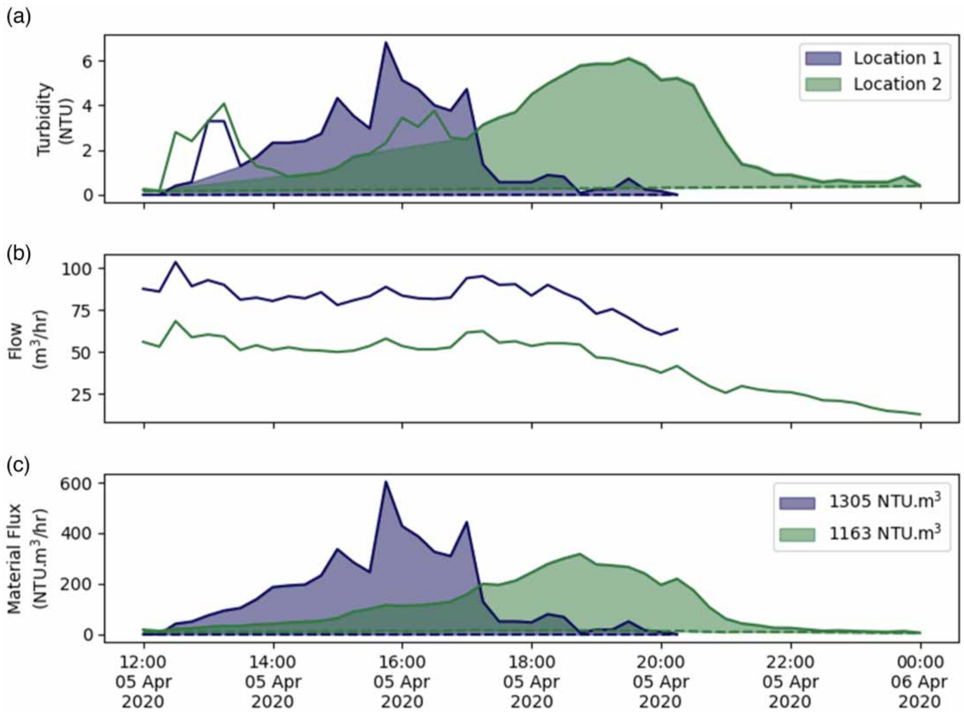


Figure 4 | Material flux is calculated from turbidity and flow time series data in order to quantify material moving past the sensor locations during an event. Turbidity event responses at each location with turbidity (a), flow (b), and net material flux (c).

chlorine residual concentration data (Figure 3(a)) was used to confirm hydraulic connectivity between two monitoring locations by Pearson's cross-correlation coefficient (PCC, Figure 3(b)). Determining the highest PCC for a sliding 4-week window determined location 1 to be approximately 3.5 h upstream of location 2.

Comparison of the turbidity time series data, shown in Figure 4(a), shows that this event started with an initial turbidity spike that occurred simultaneously at both locations (unshaded part of Figure 4(a)), followed by a more prolonged secondary response with an observed offset between event peaks that matches the transit time derived from the chlorine data. Visual assessment of the turbidity signals suggests that with extended higher levels of turbidity the event had worsened at location 2 and hence suggesting this is a local event with material being mobilised from the pipe internal surface between the locations. However material flux analysis shows this to be incorrect. With addition of flow data (Figure 4(b)), material flux analysis shown in Figure 4(c), calculated by multiplying flow and turbidity at each time step, estimates that around 10% more material traversed location 1 compared to location 2 (1,305 NTU·m^3 versus 1,163 NTU·m^3). This indicates that the source of this event is primarily upstream of Location 1, with the material entrained in the bulk flow passing through this network section with some being lost due to some low demand off-take connections. It should be noted that this calculation was based on the shaded area of Figure 4(a), the early (excluded) spikes in turbidity where likely due to material mobilisation local to the instrument locations but was not the dominant issue in this case study.

This case study demonstrates the increasing insight and confidence obtained from confirming hydraulic connectivity of sensor locations. Either turbidity sensor alone could have been neglected or assumed to be faulty. That the derived transit time also matches the time between event peaks increases confidence further. This case study also demonstrates the value in combining parameters when analysing turbidity events, in this case turbidity and flow. Interpretation of turbidity data alone misleadingly suggests a predominantly local event with the section between the monitors contributing discolouration material. It is the calculation and comparison of material flux which provides the most valuable information indicating that the dominant source and root-cause is upstream. Thus this case study demonstrates the multiplicative nature of the increase in insight and confidence obtained with MPMS analysis.

3.2. Case study 2 – MPMS alarm event following mains flow increase with associated customer contacts

This case study focuses on a discolouration event, this time combining flow and turbidity at three connected locations, as shown in the simple schematic in Figure 5 with the addition of customer contact data. Figure 6 shows the DWDS turbidity data from three connected sensor locations, all installed at offshoots from a central trunk main where a sudden increase in flow was observed (Figure 6(a)). The event (Figure 6(b)) caused over 130 discolouration contacts within 3 days (Figure 6(c)), with 31 of these contacts found to be customers directly downstream of these sensor locations. Contact data is often lagged, in the following figures it is plotted at midnight for the day the calls were received. SPSS analysis of the individual turbidity time series (Figure 6(b)) would have indicated an alarm-level event (NTU >4) at each of the three location, but this each alone would have been of low confidence.

Looking across the three sensors, which were confirmed to be connected via cross-correlation of chlorine data (not included to avoid repetition) increases confidence that this was a real event. Incorporating the mains flow data (Figure 6(a)) suggests that the discolouration was due to the temporally coincident spike in flow, greater than normally experienced. From the turbidity data alone, risk would likely have been rated similar for L1 and 3 and greater for L2. Material flux analysis during the event, Figure 7, confirms that L2 posed the greatest downstream potential for discolouration risk with more than ten times and double the amount of mobilised material traversing here compared to L1 and L3, respectively. Flux analysis significantly downgrades the discolouration potential of L1. The flux based assessment of downstream impact is confirmed in the lagged customer contacts attributed to each offshoot from the trunk main (Figure 7(d)). If a system of MPMS analysis, as set out here, had been operational in near real-time this event could have been identified early with high confidence, as being due to an increase in flow, with flux analysis used to prioritised mitigation efforts towards the network below L2 and away from L1.

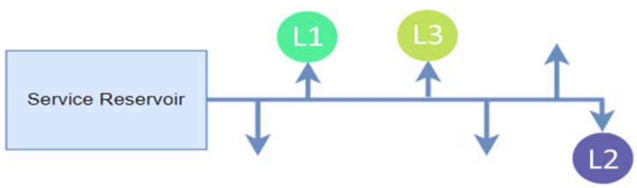


Figure 5 | Simplified network schematic showing three different sensor locations at offshoots to a trunk main section.

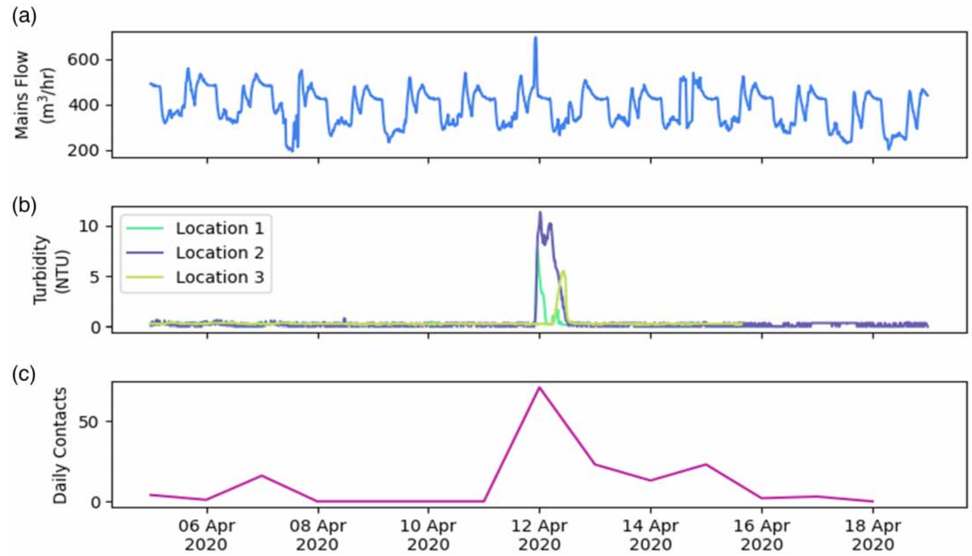


Figure 6 | Hydraulically induced turbidity response seen within the wider context of 1 week pre and post event. Mains flow (a), turbidity at the three locations (b), and network daily discolouration contacts (c).

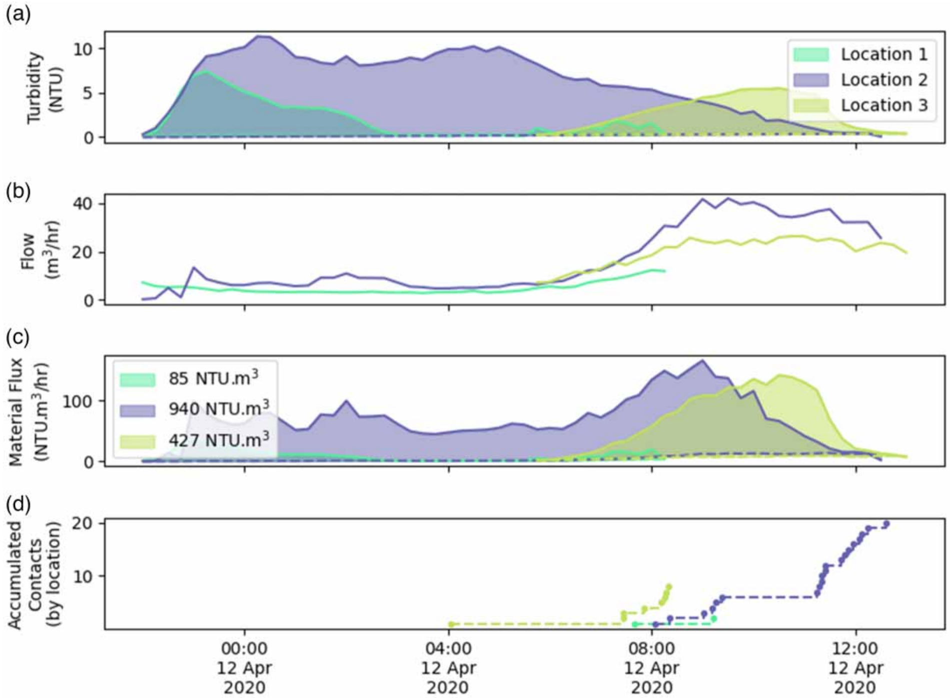


Figure 7 | Material flux calculated at three locations during event and associated customer contacts. Turbidity event at all three locations with the net turbidity in (a), flow (b), net material flux (c), and accumulated customer contacts downstream of each location (d).

3.3. Case study 3 – SPMS analysis of six turbidity sensors in single main

This case study features a single trunk main with only 2 small offtakes along its nearly 70 km length. Six turbidity sensors were installed as shown in Figure 8 to record any turbidity responses prior to and during planned maintenance work. Unlike more complex network configurations, hydraulic connectivity is assumed (and confirmed by observation of turbidity profile tracking) in this case study. However, the lack of chlorine data prevents transit time estimation and limits analysis confidence. The

Figure 8 | Simplified network schematic showing locations 1–6 along a single main.

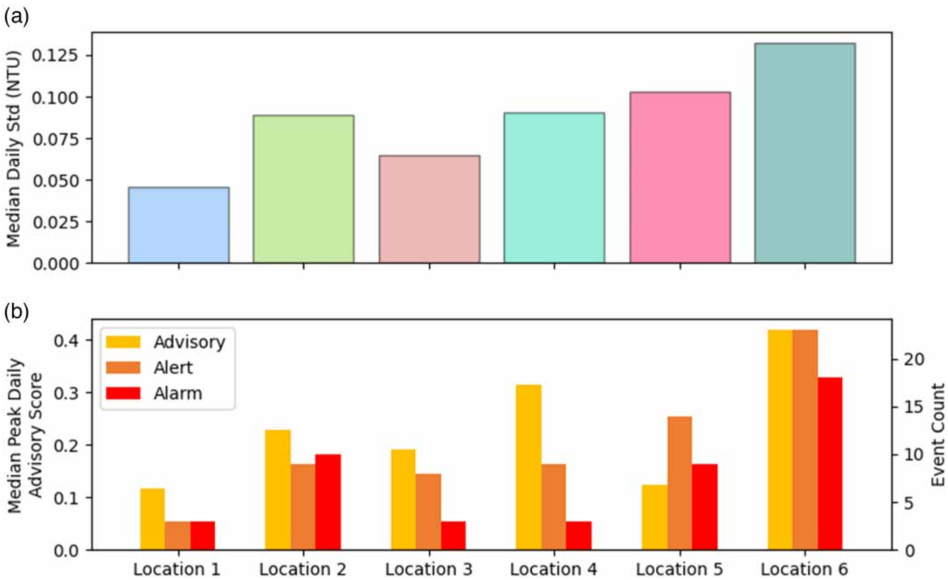


Figure 9 | Ranking of discolouration risk per sensor location using median daily standard deviation and the turbidity event scale. Median daily standard deviation for locations 1–6 (a) and median peak daily advisory score (LHS *y*-axis and yellow bars) and number of alert (>2 NTU, orange bars) and alarm (>4 NTU, red bars) events (RHS *y*-axis) (b).

median daily turbidity standard deviation was calculated using data from four weeks leading up to the conditioning exercise and is found to increase along the main (Figure 9(a)), indicating accumulating discolouration material. The turbidity event scale also shows both the frequency of alert and alarm events as well as how the daily peak advisory scores increase towards the downstream end (Figure 9(b)), indicating the compounding discolouration magnitude.

Turbidity responses are seen at each sensor during a conditioning exercise across multiple days (Figure 10). Approximate transit times between sensors are estimated by visually comparing and matching distinct features of the turbidity responses. Using the flow data from a meter located near the start of the main and flux analysis shows that most material mobilised during this event is found at the final two sites 5 and 6 (Figure 11). This analysis shows that there was additional material mobilised between locations 4 and 5, suggesting increased risk at this end of the network. However, without the precise flow data at each location, it is not possible to know exactly how much the flow at locations 4–6 is being overestimated due to the two offshoots after location 3.

This case study showcases the value in having several turbidity sensors in a connected DWDS section, in this case identifying where the discolouration risks are. Of course, all of these approaches can be applied to any of these sensors in a SPSS analysis, but it is the comparison which yields potentially the most useful network insights. However, the analysis is limited by the lack of availability of more flow data.

3.4. Case study 4 – MPMS dimensionality reduction and anomaly detection

This case study focuses on two sensor locations each with eight available parameters to examine additional analytics that are enabled with this increase in parameters. Note that though these sensor locations were within the same network, they were not hydraulically connected and therefore a schematic is not included. Dimensionality reduction using PCA (Dunia *et al.* 1996; Aggarwal 2016) is applied to two multi-parameter water quality sensor datasets, reducing the dimensions from eight

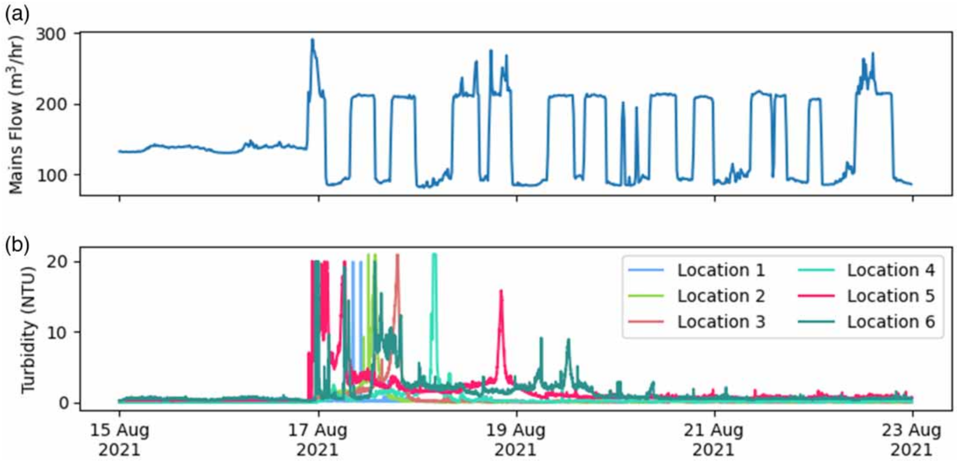


Figure 10 | Mains flow and network turbidity responses during a flow conditioning exercise. Upstream mains flow (a) and turbidity time series at each location (b).

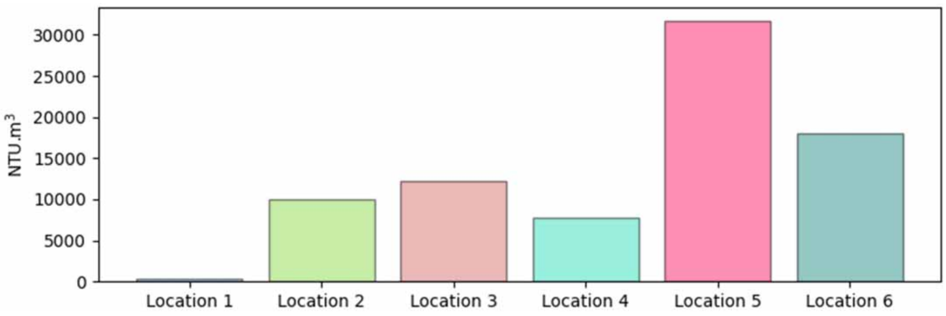


Figure 11 | Total material passing each location (material flux) during the conditioning exercise shown in Figure 10.

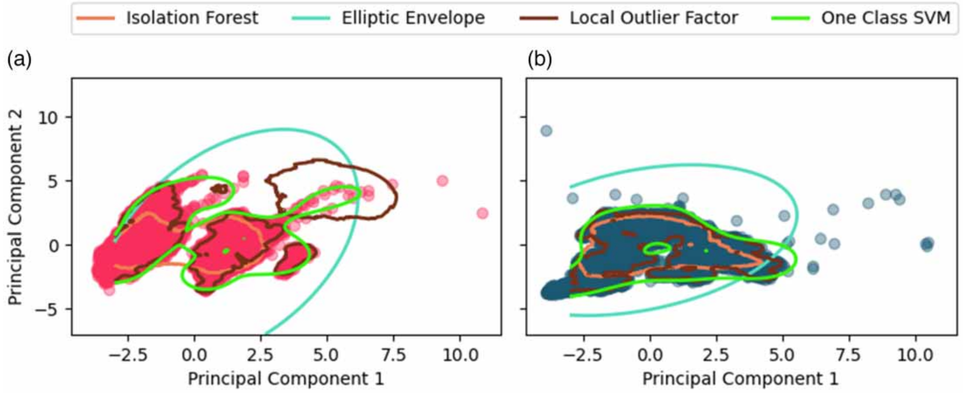


Figure 12 | Unsupervised anomaly detection techniques compared for how well they fit the first two principal components after dimensionality reduction performed on eight-parameter sensors. Scatter plots of two principal components for location H (a) and I (b), with boundary lines shown for unsupervised anomaly detection methods isolation forest, elliptic envelope, local outlier factor and one-class SVM.

parameters down to two principal components (Figure 12). This is done to enable unsupervised (i.e. automated) anomaly detection. Figure 12 shows the boundaries around normal data automatically determined by four different algorithms: isolation forests (Liu *et al.* 2008), elliptical envelopes (Rousseeuw & Driessen 1999), LOF (Breunig *et al.* 2000), and OCSVM

(Shin *et al.* 2005). Quantitative assessment is not possible, as what is a true positive, false negative etc. is unknown. For each of these algorithms, a contamination factor must be specified which dictates how much of the dataset is anomalous. Various different contamination factors ranging from 0.1 to 0.001 were tested out in order to find the best fit. From visual, qualitative inspection the OCSVM with a contamination factor of 0.001 was the most suitable of the four methods included and is therefore applied as an anomaly detection algorithm to the time series data from these sensors (Figure 13). This approach is found to detect several events of interest in the data, including turbidity spikes and drops in ORP, that were not identified by single-parameter methods such as Gleeson *et al.* (2024) and with increased confidence. This demonstrates the potential of this approach to automatically detect subtle network events and showing what is possible with increased parameter size enabling enhanced data fusion.

4. DISCUSSION

This research demonstrates how water quality time series data from DWDS can be transformed into actionable information to support improved management of distributed drinking water quality. A particular focus on network discolouration events was driven by discolouration being the most pervasive water quality issue in DWDS, along with turbidity being the most measured parameter in the datasets provided. The methods demonstrated to analyse turbidity time series data also have applicability to other parameters. That this research focused entirely on detecting real DWDS events represents a major advance from the common practice of artificially inserting events on top of measured or simulated data. The increased insight resulting from the combination of different parameters and multiple senor locations (MPMS) has been demonstrated and is discussed further in this section, along with the implications for WSP with regards to both proactively and reactively protecting drinking water quality in DWDS.

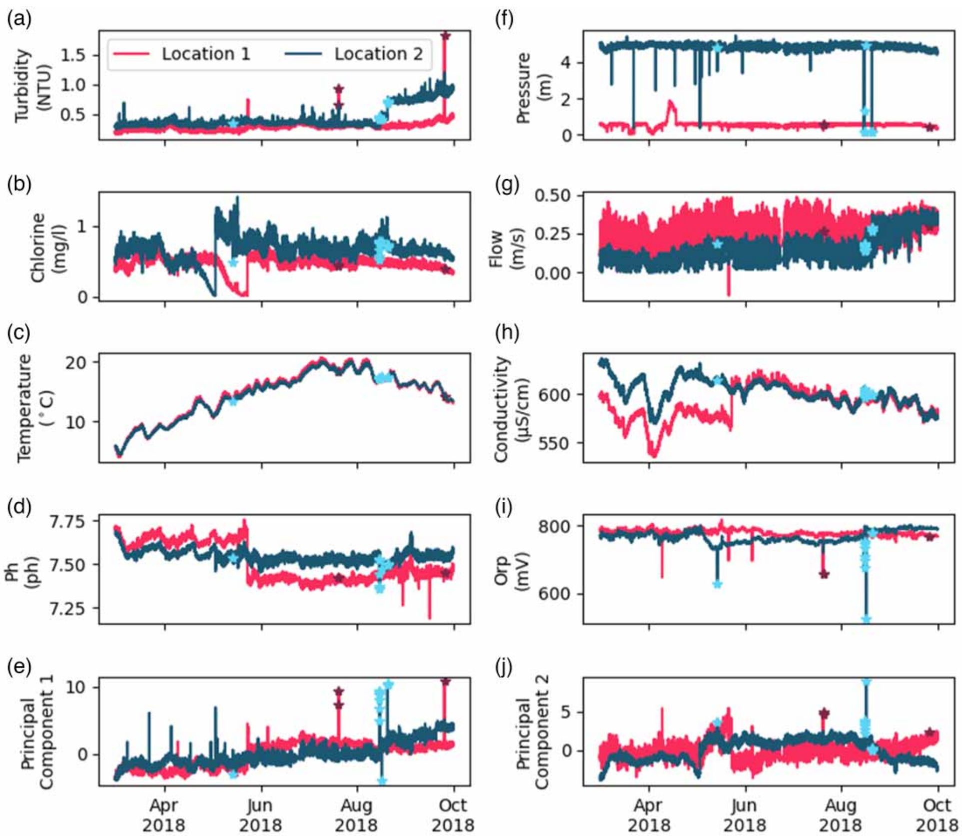


Figure 13 | OCSVM detected anomalies shown on original eight-parameter time series for both sensors. Two unconnected eight-parameter water quality time series from March to October with turbidity (a), chlorine (b), temperature (c), pH (d), pressure (f), flow (g), conductivity (h), ORP (i) and two principal components in (e) and (j), respectively. The red and blue stars indicate where anomalies have been observed in locations 1 and 2, respectively.

4.1. Multiplicative value of multiple parameters and multiple sensors

The increase in value from having multiple sensors was demonstrated with connectivity derived from cross-correlation (Gleeson *et al.* 2023a) used to improve the data quality assessment of individual sensors and parameters. The increased confidence impacts the subsequent analytics. For example in the first two cases (Sections 3.1 and 3.2) network scale events were confirmed as real, as opposed to local events or sensing errors. This logic is applicable to parameters other than turbidity, where individually a sudden unexpected change could indicate either a sensing error or a local event. The same point can be made for having multiple parameters measured at a single location, and there are some particular combinations of parameters that can be combined to increase insight, such as flow rate and turbidity to determine material flux. However, it was only with the availability of both parameters and multiple sensor locations (MPMS) that a multiplicative jump, not only in confidence, but in obtainable insight regarding the root-cause of water quality events was seen (as previously defined multiplicative refers to the increase in value being greater than adding together the individual values). This increase in value is observed across four different DWDS water quality case studies with their varied nature providing different insights described qualitatively. This is not amenable to a consistent set of quantitative and comparable metrics and the business case for rollout would need to be application-specific metrics including cost savings, as well as contextual factors such as company targets and regional regulations.

Case study 1 (Section 3.1) demonstrates the transformative power of having confirmed-connected locations and both locations having flow rate and in this case turbidity data, which combine to enable the tracking of discolouration material flux between the locations. Though it would be challenging to automate this kind of analysis, which included removal of the initial localised turbidity spike, it would not be difficult to automatically check known-connected sensor locations against a corresponding event. Case study 2 (Section 3.2) used material flux to compare which mains and offshoots received the most discolouration material during a hydraulically induced discolouration event. That the sensor location with the highest total discolouration material also had the most associated contacts validates this as a measure of downstream discolouration risk. The dramatic increase in value from MPMS analysis seen in case study 1 is again repeated in case study 2, although the addition of a third sensing location does not necessarily have the same level of increased value as the vital second location that enables event tracking to take place. Whether the additional value from a third connected location is greater than the additional cost of deploying this third sensor depends on what insight is required and whether three locations have been identified as of interest.

Case study 3 (Section 3.3) demonstrated how only having turbidity at multiple locations may limit accurate tracking of an event. Though in this single straight main case connectivity could be assumed, the lack of transit time meant visual assessment was relied upon to track a network-wide turbidity event. This case study does show how the availability of multiple connected turbidity sensors enables discolouration risks to be mapped and compared across entire DWDS sections, with the region between sensors 4 and 5 found to have increased material mobilisation. This case study hence demonstrated multiplicative increase in value with additional sensors. However, it could be argued that similar analysis would have been possible with only three or four sensor locations, suggesting that the degree of the multiplicative effects do not continue. A case looking at eight-parameter sensors was included in case study 4 (Section 3.4), where dimensionality reduction and unsupervised anomaly detection was shown to be an effective way to identify unusual subtle events in any parameter, showing the value in having high dimension water quality time series. Though it is difficult to quantify the increase in value with additional parameters, as this is very dependent on what insights are desired, this case study shows an example of what can be done. With more water quality parameters and newer technologies emerging such as real-time bacteriological sensors, the potential for combining and fusion different water quality parameters are high.

These case studies demonstrate that the increase in value and insight obtainable does not increase linearly from SPSS to MPMS analysis, but instead a multiplicative increase is seen, with a particularly significant jump when moving from single sensor to having a comparable second sensor. This impacts deployment strategies as the additional value from deploying more than one connected location is likely to be greater than the additional cost. When it comes to analysing a water quality event in a DWDS, knowing what sensors are hydraulically connected and the approximate transit times involved is transformative in its power. This places significant importance on gaining an understanding of the hydraulic connectivity between sensor locations. The multiplicative increase seen when moving from single-parameter single-sensor to multiple parameter multiple sensor analytics would not be expected to continue, or the multiplicative effect be as great, with the addition of more and more sensors and parameters, as suggested from case study 3. It is likely the multiplicative increases would tail off and plateau with increasing numbers of sensors and parameter. Datasets to quantify this for meaningful real-world examples are not available, and would be a function of what insight is desired.

4.2. From reactive to proactive management of network water quality events

Unpredictable and undesirable DWDS water quality events are thankfully rare but are inevitable due to aging, complex infrastructure. Therefore, digitalisation of DWDS must include the ability to accurately detect and understand such events in a timely manner. The ability to take effective action following a detected discolouration event for example is dependent on how quickly and confidently the event is detected and the time before the discoloured water reaches customers. An alarm event (using the turbidity event scale developed by Gleeson *et al.* 2024), seen at two or more connected locations and therefore of high confidence, should prompt immediate action. However, the lead time required for WSP to perform mitigating actions that can halt discoloured water already on route to customers is likely greater than would be available. This is where edge computing of the turbidity event scale could function to rapidly enable such alerts and warnings to be sent out. Relying on waiting for the data to be uploaded to a central server before analysis reaches the alarm category means many such events would reach customers before action is taken. Once an alarm is raised, it is important to understand the route cause so that appropriate action is taken. Material flux has been shown to be central to the route cause analysis reported here, able to detect and confirm the source of DWDS water quality events. This represents a clear improvement over reliance on subjective retrospective analysis of customer contact information, providing WSP with actionable information that can lead to improved future management of water quality. It should be noted that material flux estimates the material mobilised during an event, the discolouration risk potential. To obtain a full estimate of risk, this should be factored by the number of downstream customers likely to be impacted, the discolouration risk consequence.

Improved water quality event detection, root-cause determination and estimation of downstream risk all represent an improvement over the status quo yet they remain largely reactive in nature. It is highly desirable to move towards more proactive management approaches, i.e. event prevention. The turbidity advisory score approach developed in Gleeson *et al.* (2024) has shown promise for flagging low-level increases in turbidity that would commonly be ignored due to low data confidence. Case study 3 (Section 3.3) showed that the number of alert and alarm events was seen to broadly increase with transit time/distance through the single straight network section, as well as the median peak daily advisory score proactively indicating increasing potential for discolouration with time/distance. Using the highest daily advisory score is an obvious way to simplify the advisory score time series, and reporting the median value of this would provide information on the average level for a given day. The median daily standard deviation was also seen to roughly increase through this network section and this demonstrates the promise of this metric to proactively estimate discolouration risk. In particular as this is a measure of diurnal variability of turbidity which may to be linked to daily hydraulics as a known precursor of discolouration events (Husband *et al.* 2008). Whether the analysis is reactive or proactive, the multiplicative benefits of MPMS are equally important and applicable.

5. CONCLUSIONS

To enable wider exploration of these findings and support future developments in DWDS water quality monitoring, the datasets utilised in this study are made openly available, aside from case study 4 which is restricted for commercial purposes (https://doi.org/10.15131/shef.data.28045628.v1). This research utilising data sets from operational DWDS highlights the potential value of continuous water quality sensors to provide actionable information for management of DWDS. By developing and applying novel analytics and fusing MPMS water quality data, this research has shown how it is possible to understand and track water quality changes within complex DWDS.

The key findings are summarised as follows:

- The level of insight obtained from sensor data increases multiplicatively as analysis moves from single-parameter single-sensor approaches to the integration of multi-parameters and multi-sensor.
- Using turbidity, chlorine, and flow data from multiple connected locations facilitates accurate discolouration event tracking, providing valuable information about both the source (root-cause) and destination (impacts) of discolouration material.
- The turbidity advisory event score and the daily standard deviation analytics can enable a shift from reactive to proactive discolouration management.

The major overarching outcome of this work is the demonstration that the level of insight obtainable from water quality sensor data increases multiplicatively with the integration of multiple parameters from multiple sensor locations. This finding will help inform the intelligent deployment and analysis of networks of water quality sensors, ultimately leading to improved understanding and proactive management of DWDS. By demonstrating how to obtain actionable, operational insights from real-world case studies using novel analytics this research represents a significant step forward in the field of water quality monitoring and management.

Future work can build on this research by developing a more complete source-to-tap understanding that includes data taken from catchment areas, treatment works and customer taps. This would enable even more data fusion to enhance MPMS source-to-tap system monitoring. Additionally, future work can investigate and validate the proactive analytics presented, evidencing that such metrics can be used to operate DWDS more efficiently and less reactively. Both of these areas together represent promising avenues for enabling enhanced digital water quality monitoring within DWDS.

ACKNOWLEDGEMENTS

This research has been supported by an Engineering and Physical Sciences Research Council (EPSRC) studentship as part of the Centre for Doctoral Training in Water Infrastructure and Resilience (EP/S023666/1) with support from industrial sponsor Siemens UK, Anna Taliana and Paul Gaskin of Welsh Water, Jez Downs of Southern Water, and Graham Knowles of Scottish Water.

DATA AVAILABILITY STATEMENT

The datasets utilised in this study are made openly available, aside from case study 4 which is restricted for commercial purposes. The data is available at https://doi.org/10.15131/shef.data.28045628.v1.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Aggarwal, C. C. (2016) *Outlier Analysis*, 2nd edn. New York, NY: Springer New York.

Aisopou, A., Stoianov, I. & Graham, N. J. D. (2012) In-Pipe water quality monitoring in water supply systems under steady and unsteady state flow conditions: a quantitative assessment, *Water Research*, **46** (1), 235–246. doi: 10.1016/j.watres.2011.10.058.

Boxall, J. B. & Saul, A. J. (2005) Modeling discoloration in potable water distribution systems, *Journal of Environmental Engineering*, **131** (5), 716–725. doi: 10.1061/(ASCE)0733-9372(2005)131:5(716).

Boxall, J., Blokker, M., Schaap, P., Speight, V. & Husband, S. (2023) Managing discolouration in drinking water distribution systems by integrating understanding of material behaviour, *Water Research*, **243**, 120416. doi: 10.1016/j.watres.2023.120416.

Breunig, M. M., Kriegel, H. P., Ng, R. T. & Sander, J. (2000). 'LOF: identifying density-based local outliers', *Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data*. New York, NY, USA. ACM, pp. 93–104.

Cook, D. M., Husband, S. & Boxall, J. B. (2016) Operational management of trunk main discolouration risk, *Urban Water Journal*, **13** (4), 382–395. doi: 10.1080/1573062X.2014.993994.

Dunia, R., Joe Qin, S., Edgar, T. F. & McAvoy, T. J. (1996) Use of principal component analysis for sensor fault identification, *Computers & Chemical Engineering*, **20**, S713–S718. doi: 10.1016/0098-1354(96)00128-7.

DWI (2018) *The Water Supply (Water Quality)(Amendment) Regulations 2018 SI No. 706*. London.

DWI (2023) *Drinking Water 2022: the Chief Inspector's Report for Drinking Water in England*. London.

EU (1998) *98/83/EC of Council of 3rd November 1998 on the Quality of Water Intended for Human Consumption*. Council of the European Union in Brussels, Belgium

Furnass (2015) *Modelling Both the Continual Accumulation and Erosion of Discolouration Material in Drinking Water Distribution Systems*. Sheffield, UK: The University of Sheffield.

Gaffney, J. W. & Boult, S. (2012) Need for and use of high-resolution turbidity monitoring in managing discoloration in distribution, *Journal of Environmental Engineering*, **138** (6), 637–644. doi: 10.1061/(ASCE)EE.1943-7870.0000521.

Gleeson, K., Husband, S., Gaffney, J. & Boxall, J. (2023a) A data quality assessment framework for drinking water distribution system water quality time series datasets, *Journal of Water Supply: Research and Technology-Aqua*. 72 (3), 329–347. doi: 10.2166/aqua.2023.228.

Gleeson, K., Husband, S., Gaffney, J. & Boxall, J. (2023b) Determining the spatio-temporal relationship between water quality monitors in drinking water distribution systems, *IOP Conference Series: Earth and Environmental Science*, **1136** (1), 012046. doi: 10.1088/1755-1315/1136/1/012046.

Gleeson, K., Husband, S., Gaffney, J. & Boxall, J. (2024) Algorithms to mimic human interpretation of turbidity events from drinking water distribution systems, *Journal of Hydroinformatics*, **26** (1), 143–161. doi: 10.2166/hydro.2023.159.

Husband, P. S., Boxall, J. B. & Saul, A. J. (2008) Laboratory studies investigating the processes leading to discolouration in water distribution networks, *Water Research*, **42** (16), 4309–4318. doi: 10.1016/j.watres.2008.07.026.

Kennedy (Doronina), A., Husband, S., Boxall, J. & Speight, V. (2024) A metric for drinking water service reservoir performance as a sink or source of material, *AQUA – Water Infrastructure, Ecosystems and Society*, **73** (5), 999–1012. doi: 10.2166/aqua.2024.039.

Li, D., Chen, D., Jin, B., Shi, L., Goh, J. & Ng, S.-K. (2019) MAD-GAN: multivariate anomaly detection for time series data with generative adversarial networks. In: Tetko, I., Kurkova, V., Karpov, P., and Theis, F. *Artificial Neural Networks and Machine Learning – ICANN 2019: Text and Time Series*, Cham: Springer, pp. 703–716.

Liu, F. T., Ting, K. M. & Zhou, Z.-H. (2008). 'Isolation forest', *2008 Eighth IEEE International Conference on Data Mining*. IEEE, pp. 413–422

Mounce, S. R., Mounce, R. B. & Boxall, J. B. (2012) Identifying sampling interval for event detection in water distribution networks, *Journal of Water Resources Planning and Management*, **138** (2), 187–191. doi: 10.1061/(ASCE)WR.1943-5452.0000170.

Mounce, S. R., Gaffney, J. W., Boult, S. & Boxall, J. B. (2015) Automated data-driven approaches to evaluating and interpreting water quality time series data from water distribution systems, *Journal of Water Resources Planning and Management*, **141** (11), 37–39. doi: 10.1061/(ASCE)WR.1943-5452.0000533.

Muharemi, F., Logofătu, D. & Leon, F. (2019) Machine learning approaches for anomaly detection of water quality on a real-world data set, *Journal of Information and Telecommunication*, **3** (3), 294–307. doi: 10.1080/24751839.2019.1565653.

Murray, R. & Haxton, T. (2010) *Water Quality Event Detection Systems for Drinking Water Contamination Warning Systems – Development, Testing, and Application of CANARY*. Cincinnati, OH: U.S. Environmental Protection Agency.

Perelman, L., Arad, J., Housh, M. & Ostfeld, A. (2012) Event detection in water distribution systems from multivariate water quality time series, *Environmental Science & Technology*, **46** (15), 8212–8219. doi: 10.1021/es3014024.

Rousseeuw, P. J. & Driessen, K. V. (1999) A fast algorithm for the minimum covariance determinant estimator, *Technometrics*, **41** (3), 212–223. doi: 10.1080/00401706.1999.10485670.

Shin, H. J., Eom, D.-H. & Kim, S.-S. (2005) One-class support vector machines – an application in machine fault detection and classification, *Computers & Industrial Engineering*, **48** (2), 395–408. doi: 10.1016/j.cie.2005.01.009.

UN-INWEH (2020) *Water and Migration: A Global Overview*. Canada: Hamilton.

USEPA (2018) *2018 Edition of the Drinking Water Standards and Health Advisories Tables*. Washington, DC, USA: U.S. Environmental Protection Agency, Washington, DC, USA.

Weston, S. L., Collins, R. P. & Boxall, J. B. (2021) An experimental study of how hydraulic transients cause mobilisation of material within drinking water distribution systems, *Water Research*, **194**, 116890. doi: 10.1016/j.watres.2021.116890.

WHO (2017) *Guidelines for Drinking Water Quality*. World Health Organization in Geneva, Switzerland.

First received 7 January 2025; accepted in revised form 23 June 2025. Available online 1 July 2025