



Digital Water

Digital dynamic resilience
for wastewater treatment
processes: exploiting real data
for long term resilience

Digital Water

Digital dynamic resilience for wastewater treatment processes: exploiting real data for long term resilience

Authors

Timothy Grant Holloway *Senior Scientific Officer at University of Portsmouth School of Civil Engineering and Surveying*

John Barry Williams *Professor of Environmental Technology at University of Portsmouth School of Civil Engineering and Surveying*

Djamila Ouelhadj *Professor of Operational Research at the University of Portsmouth Department of Mathematics*

Gong Yang *Process Capacity Manager at Southern Water Services Ltd*

Ben Martin *Lead Research Scientist at Thames Water*

Matthew Wade *Science Lead: Wastewater Research and Development, Environmental Monitoring for Health Protection, Data Analytics and Surveillance at the UK Health Security Agency*

© 2022 International Water Association

Published by the International Water Association. All rights reserved.

Requests for permission to reproduce or translate this material — whether for sale or non-commercial distribution — should be directed to the IWA Media Office via the website (www.iwa-network.org).

All reasonable precautions have been taken by the International Water Association to verify the information contained in this publication. However, the published material is being distributed without warranty of any kind, either expressed or implied. The responsibility for the interpretation and use of the material lies with the reader. In no event shall the International Water Association be liable for damages arising from its use.

Foreword



The digital transformation under way in the water sector encompasses improvements in function, viability, and overall service provision by utilities in the face of ageing infrastructure, increased frequency of extreme events, urbanisation and population growth, and unforeseen global events.

Looked at from that perspective, one could say that the *raison d'être* of digitalisation is to secure resilience – resilience of drinking water supply, wastewater treatment, stormwater management, and much more. As growing numbers of utilities begin to incorporate digital technologies into their daily operations, the benefits become increasingly evident. But in parallel to this, new challenges also emerge.

The International Water Association's (IWA) 5-year Strategic Plan 2019-2024 highlights the need for innovation to address global water challenges. With this strategic outlook in mind, IWA's Digital Water Programme is pleased to share this publication "Dynamic resilience for wastewater treatment processes: exploiting real data for long term resilience". This white paper takes a look at the concept of dynamic resilience through the lens of wastewater processes and resource recovery facilities while highlighting the perspectives of public health and industry professionals. With the unpredictability of today's challenges, a solution's resilience is equivalent to its efficiency.

The approach presented in this paper gives insight into how a system or process responds to a stressor/event and how this can be used to predict future events, eventually resulting in more streamlined and proactive operation. It emphasises the need for consistent and quality data collection, while presenting a use for large data silos, which often tend to be overlooked. It provides a basis for encouraging utilities and companies to implement sufficient and effective instrumentation. It also aids in the evaluation of digital transformation.

IWA is actively engaging across the international water sector to build support for a smarter approach to water management, highlighting the advantages of digitalisation as a key enabler. Tapping into the extensive knowledge of our expert members, IWA can function as a catalyst for water and wastewater utilities during their journey towards the uptake of digital technologies. To support this journey, the IWA Digital Water white paper series is providing insights into core aspects of the digital space. Thanks to this latest addition on the concept of dynamic resilience, professionals can predict and plan for future significant events with more confidence, while prescribing proactive solutions.

The initiative reflects IWA's wider outlook: we believe that, by joining forces and sharing experiences through collective actions, our sector and our society can respond to critical challenges and emerge far more resilient than we have previously imagined possible.

Kalanithy Vairavamoorthy

Executive Director of the International Water Association

Summary

With societal (e.g., COVID-19) and climatic factors coinciding with increasing regulatory pressures, the resilience of wastewater networks and infrastructure is reducing globally. Historically, water companies have relied in reserve capacity, but are now being forced to manage extreme dynamic responses as wastewater assets react new stressors. An example of this is rainfall intensity, which has already increased from 12 to 24 % (Fischer et al., 2014) and has been commonly followed by prolonged dry periods driven by climate change (NASA, 2016). These dramatic variations generate complex dynamic changes and can drastically reduce the resilience of networks and, in turn, of the network water resource recovery facilities (WRRF). Without unified quantification methods, it is impossible to compare the resilience of different wastewater processes or systems, when exposed to climate and societal stressors. Also, the complexity of dynamic changes makes it virtually impossible to simulate the numerous dynamic factors that combined cause these reductions in resilience.

To avoid possibly cumbersome modelling and simulation of possible scenarios, dynamic resilience uses actual WRRF data to visualise zones of process stress and resilience as a heat map. The methods presented in this white paper separate stressors present in water company data as the 'cause' of an event, and the 'effect', whether a WRRF experiences process stress or resilience as a result. This separation of stressors and process stress is key to isolating the cause of an event then its manifestation as the 'effect'. This separation of the stressor and process stress requires data feedback from WRRF process and systems. Data generated by water companies is ideal for computation of dynamic resilience in response to extreme events, where the cause (stressor) and effect (process stress) can be separated. This data is generated in vast quantities daily (typically < 1 h intervals) and is used to make operational decisions, but often remains in silos, or as described by Aguado et al. (2021), 'data graveyards'. Another challenge is that WRRF data can be difficult to interpret when instruments are poorly maintained or installed incorrectly (Grievson, 2020), but meaningful observations can still be made to interpret resilience metrics. Therefore, this data must be exploited to understand the dynamic resilience. Without data (real-time or from silos) connecting a WRRF or process to resilience, evaluations may remain theoretical and iterative, which is computationally intensive.

This white paper starts by describing the historical context of resilience, before moving onto the dynamic resilience of wastewater processes and WRRF. Real-world examples of societal and process related resilience from industrial and academic experts are provided, which discuss the challenge of generating data under uncertainty of ageing infrastructure. A case study is then presented on dynamic resilience using actual WRRF data. The case study shows how actual water company instrument data could be used to evaluate stressors and process stresses independently. The outcomes of dynamic resilience case studies are then presented as a series of contoured heat maps.

This section covers the fundamental and historical context of resilience and its evolution within the water industry globally.

The fundamentals of resilience for wastewater treatment

The word resilience dates back to the 1620s, described as the ‘act of rebounding’, i.e., the ability to recover from an external event (Harper, 2019). By definition, the term rebound indicates that an external event causes a system to deviate from its initial reference position, and must be reconciled for an event to be considered complete. Classical resilience theory, originated from social sciences, focusing on ecological resilience in predator-prey systems, where a system absorbs change until moving to a completely new state as described by Canadian ecologist Crawford Holling (Holling, 1973). This description was later expanded to include engineering resilience, which focuses on maintaining stability close to an equilibrium steady state. An example of engineering resilience is a set point, where the system is controlled to maintain predictable operation close to user defined optimum.

Wastewater systems can be a combination of the two types of resilience (ecological and engineered). Extraneous events shift the wastewater collection systems to a new operating state and, as result, the system performance is controlled, in order to manage undesirable process upsets or disturbances. Using the example of an activated sludge (AS) system, the microbial ecology is controlled by an engineered system of mechanical/electrical components (aeration and pumps). Therefore, a more accurate classification of a biological treatment process would be engineered ecology, where process engineers apply engineering principals to control biological ecology. Wastewater catchments can also behave ecologically, where systems can move to a completely different operational state as populations vary, or extreme events occur. Many of these changes in the catchment have a direct effect on the WRRF engineered ecology due to dramatic operational state changes which reduce resilience by eroding operational safety factors (reserve capacity). Therefore, to evaluate the dynamics of resilience, we must understand that we are actually managing engineered ecology (i.e., engineered systems that aims to control microbial ecology). This is where, dynamic resilience extends existing theories: it accepts that dynamic changes in resilience are both, positive (resilience) and negative (stress).

Another difficulty for resilience has been selecting an appropriate definition. A commonly accepted definition was proposed by Walker et al. (2004) as:

‘Resilience is the capacity of a system to absorb disturbance and reorganise while undergoing change so as to retain essentially the same pre-disturbance process, form, identity, and feedbacks’

This definition suggests that a system undergoing change adapts to an event before returning to its original condition (Fig. 1). However, the definition does not account for the complexity associated with biological wastewater systems,

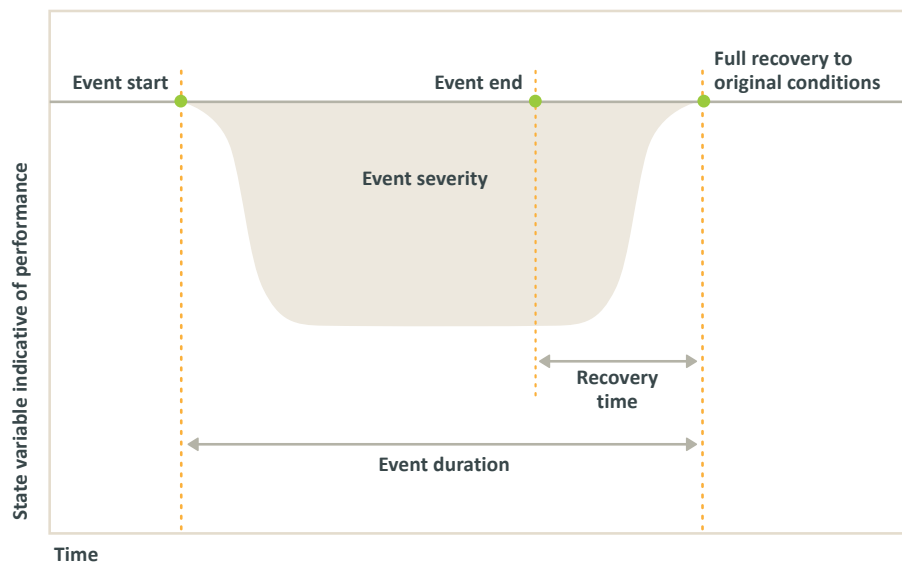


Fig. 1 Resilience to a stressor presented by Juan-García et al. (2017) adapted from Mugume et al. (2015)

which have numerous states (ecological and engineered), some temporary and some permanent. Resilience is also reduced further, by additional novel extreme states occurring outside of diurnal and seasonal patterns, which related to climate change and modifications to human behaviour. When normal operation is combined with novel stressors, simulation of their response is cumbersome, vast numbers of theoretical iterations. Therefore, if WRRF data has sufficient resolution (adequate range and quantity), it could hold clues to these novel states, where many parameters are affected by stressors, and the process stress/resilience response (dynamic resilience).

There are many interrelated factors must be considered to evaluate the dynamics of resilience. Therefore, it is crucial to not only consider wastewater infrastructure and WRRF, but also factors that lead to stressors under the following headings:

1. Political resilience
2. Economic resilience
3. Social resilience
4. Technological resilience
5. Environmental resilience
6. Legal resilience

PESTEL factors and their interactions are responsible for many of the stressors exerted on ageing assets and infrastructure. However, in times of societal adaptation and change, numerous PESTEL factors can become interrelated, generating significant complexity and uncertainty. Nevertheless, pre-existing clues of dynamic stressors and process stresses are apparent in water company transactional data and surveillance data used by government agencies to monitor COVID-19. This white paper focuses on stressors occurring from a wastewater catchment that have a significant effect on the stresses generated within a specific WRRF. As shown in Fig. 2, these direct external stressors have the greatest potential to have significant influence on wastewater volumes and concentrations.

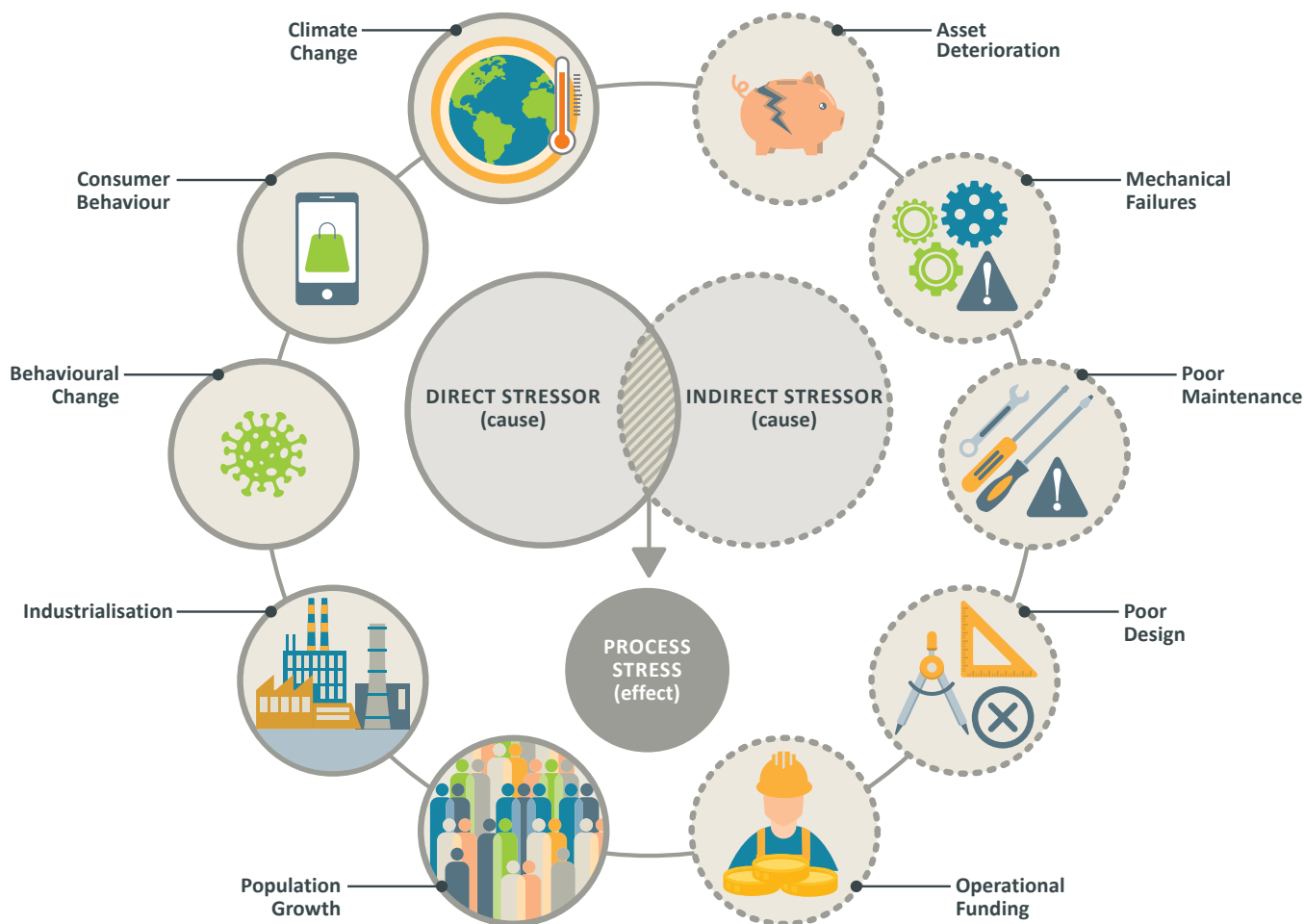


Fig. 2 Direct (external) and indirect (internal) stressors adapted from Butler et al. (2014).

The evolution of resilience as a concept in the water sector

Since the original research of Holling (1973) and Walker et al. (2004), interest in resilience has grown in all subject areas. The investigation of resilience as a determinant for water and wastewater systems has been well documented, see Butler et al. (2014). A reasonable level of success has been achieved in water supply resilience, although this is often not suitable for the complex multi-variate mechanisms, and often competing processes, associated with wastewater delivery and treatment. When wastewater is generated numerous factors are involved, for example, urban creep or groundwater infiltration to sewers can dramatically increase the flow to a receiving WRRF. The randomness and unpredictability of changes leads to significant reductions in resilience over a short period of time (i.e., hrs). Attempts have been made to circumvent this with research focussing more toward general resilience (Sweetapple et al., 2022a), which utilises a more systems of systems approach that can be highly complex. From an industry perspective, there has been growing interest in resilience as a concept by the UK water companies; however, the principles have not been fully embedded. This was exemplified by the Ofwat price review 2019 (PR19), where only two water companies provided evidence of securing the long-term resilience of their assets

(Ofwat, 2019). Therefore indicating that the challenge is not the generation of greater knowledge; but applying resilience theory and embedding its principles into daily operation.

For this to happen, dynamic changes in operation that influence resilience, should consider the use of existing WRRF data to build a knowledge base of past stressors and process stresses/resilience (dynamic resilience) in preparation to future events. For instance, to avoid potentially damaging pollution incidents, it is crucial to understand how stressors manifest leading up to such dramatic changes in wastewater volume and concentration. To understand these dynamic events, the interaction of stressors and process stresses/resilience should be considered as dynamic resilience (Fig. 3). The principle of dynamic resilience in Fig. 3 shows the stressor as having a bell shaped peak and the process stresses generated as a well defined peak concentration. Differences between stressors (cause) and process stresses (effect) occur because the WRRF behaves differently to the generated stressor due to recirculations and sludge extractions. Understanding the magnitude and duration of events has benefits, gives rise to the possibility of classifying stressor influence at the WRRF or for separate processes. It also allows for a reaction time between an event occurring (stressor) and its effect on the process (stress).

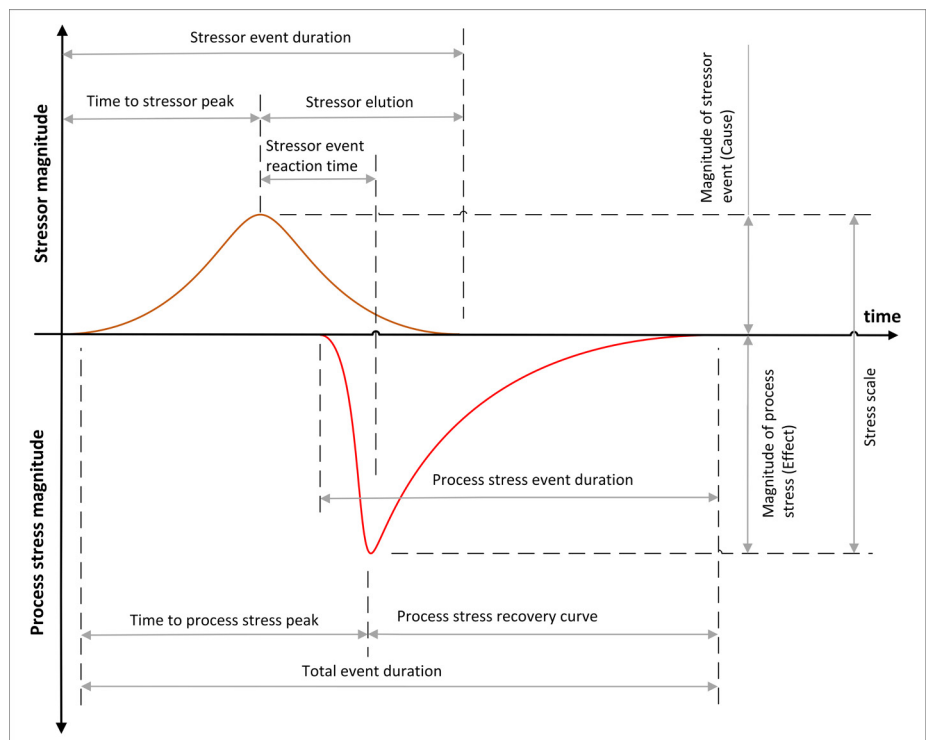


Fig. 3 Dynamic resilience diagram showing the separation of stressors and process stresses.

Experts' perspectives of resilience

The definition of dynamic resilience used in this white paper, as shown in Fig. 2 and also presented in the International Water Association (IWA) Modelling and Integrated Assessment (MIA) Specialist Group (SG) webinar (Holloway et al. 2021) is detailed below as:

“The dynamic, temporal variation of stressors and process stresses (and resilience) in response to events outside of standard operating conditions”

The following two sections provide an overview of the resilience based challenges faced by water companies and those interpreting data from wastewater-based epidemiology.

Resilience from a water company perspective

Wastewater flow data is central to understanding the dynamic resilience of wastewater infrastructure and WRRF and to understand the pressure exerted by wastewater catchments (stressors). Water companies in the UK are making great strides in understanding how their assets react to climate change while incorporating meteorological and demographic data. In this section, Dr Ben Martin speaks of the challenges associated with asset and infrastructure resilience and how Thames Water are embedding dynamic digital systems.

Improving asset and infrastructure resilience is a significant challenge for the water industry as operational disruptions become more common and difficult to predict. The most significant of these disruptions are extreme weather events, which have recently delivered a month's worth of rain in one hour. Most sewers and wastewater treatment plants are many decades old and were simply not designed to cope with the loads and temperature fluctuations recorded in recent years. Such weather events have been coupled with the COVID pandemic, which resulted in spatial disruptions to normal wastewater loads as the mobility of the population reduced during lockdowns.

Thames Water is currently working on a host of data driven projects to increase the resilience of ageing asset and infrastructure base. These digital initiatives will output control systems that can manage disruptive loads more effectively and efficiently. Additionally, a digital twin is being developed for Beckton sewage treatment works, the largest wastewater treatment plant in the UK. This brings together a number of hydraulic, pneumatic, and biological models to digitally represent its physical assets. This is expected to deliver a 10-20% reduction in workforce planning, a 30-50% reduction in predictive maintenance, and a 20-40% reduction in reactive maintenance.

A broad rollout of connected digital monitoring instruments throughout assets and infrastructure is planned. These include prediction systems so that assets can be maintained and replaced long before failure, machine learning to enable autonomous waste catchments, and open data frameworks for sharing across water companies. Linkages will also be established with meteorological and demographic datasets. These will inform operational control strategies that can respond in real time, or even ahead of time, to enable rapid recovery from events. These dynamic digital systems will ensure that as disruptions become the norm, wastewater can still be treated to exceed environmental targets.

Resilience of water management systems for public health protection

Social resilience has a key role in the protection of public health. In this section, Dr Matthew Wade writes of the challenges associated with asset and infrastructure resilience and its impact on monitoring wastewater-based epidemiology (WBE).

Developments in the water sector to embrace Industry 4.0 and digital transformation philosophy have demonstrated an evolution in the function of wastewater. While the focus of treatment and transport infrastructure has been generally on protecting the environment from harmful pollutants and, more recently, resource and energy recovery from wastewater (Daigger, 2009; Guest et al., 2009; Kehrein et al., 2020), the COVID-19 pandemic has given greater visibility to a broader function of wastewater systems, public health protection.

Wastewater monitoring as a tool for public health intervention dates to the mid-19th Century, when physician John Snow mapped data of cholera incidence in Soho, London to determine the source of the outbreak (a water pump contaminated with sewage) (Tulchinsky, 2018). The detection of sewage borne indicators of public health, commonly known as WBE, has been used to monitor a range of targets from poliovirus to illicit drug use in urban centres (Larsen et al., 2021). From the onset of the COVID-19 pandemic, the SARS-CoV-2 viral RNA was shown to both be detectable and quantifiable in sewer samples collected throughout the sewer network, typically at the inlet of treatment works, within-network, or at near-source (e.g., building scale) (Ahmed et al., 2020; Sweetapple et al., 2022b).

Given the evolution of the virus, subsequent work has also demonstrated the ability to detect its variants (Crits-Christoph et al., 2021). Once evidenced, the challenge for those working with WBE for COVID-19 was to determine the value of these datasets for public health policy and decision-making. The rapid uplift of COVID-19 science in wastewater and the fragmented nature of its utilisation across the globe means that the true value proposition of WBE as tool to complement existing measures of public health remains unproven and uncertain. Factors influencing its resilience include a lack of empirical data to understand and mitigate for wide range of uncertainties associated with the data from WBE (Wade et al., 2022), a robust understanding of the relationship between the target marker(s) of public health (Mao et al., 2020), and the general lack of standardisation and protocols to enable WBE to be implemented as a function

of public health policy (Wu et al. 2021). Nevertheless, WBE has great potential as a tool for public health protection beyond COVID and across a broad range of targets (e.g., lifestyle chemicals, pathogens, metabolites of health), settings (e.g., community-wide, critical infrastructure), environments (e.g., urban centres, low-income settings) and functions (e.g., rapid response, long-term surveillance of health trends, targeted monitoring).

For WBE to be useful in the long-term, its research, development, and use needs to be considered together with the wider efforts to ensure infrastructural and data resilience. This should be viewed as a resilience of the systems where information is collected, as a failing sewer network will inevitably lead to greater measurement uncertainty. Additionally, it is crucial to consider its ability to ensure public health resilience as the information acquired by WBE must be reliable and usable by the stakeholders receiving it. This effort must be global. Water and disease know no borders and ensuring the resilience of water systems in highly resourced regions (e.g., those with the means to embrace digital tools to manage the increasingly voluminous and valuable data streams), must be matched by initiatives to maximise the value and potential for WBE in low-income settings (e.g., development of low-cost but smart technologies (Gwenzi, 2022)).

The importance of data for the evaluation of dynamic resilience

This section evaluates the challenge of using actual stochastic data, presents possible methods for generating valuable insights, and finally evaluates dynamic resilience. It finishes with the future perspectives of dynamic resilience and how the best possible environmental outcomes can be achieved.

Data and the importance of scale: changing from micro to macro analysis

Before examples of dynamic resilience are presented, it is crucial to note some of the pitfalls of using actual WRRF data. The use of large datasets captured over multiple years can be overwhelming (e.g., 174,720 data points when logged at 15 min intervals over 5 years). Conventional concentration-time plots are not sufficient, providing poor resolution due to the variation frequency of actual stochastic WRRF data. An example of this can be seen in Fig. 4a, where aggregated boxplots of hourly WRRF influent flow over 10 years show significant variability. It also indicates that this data is not normal or lognormal, so when averages are taken (Fig. 4b), the central tendency is skewed providing inaccurate flow predictions. Therefore, significant uncertainty can be created when making statistical assumptions, particularly when data is being used as a timeseries for data-driven models or other statistical evaluations (Newhart et al., 2019). To avoid introducing significant uncertainty the entire data set must be considered (macro analysis). This also avoids the temptation to be myopic, analysing each discrete variation (micro analysis) which can also lead to erroneous outputs when performing simulations.

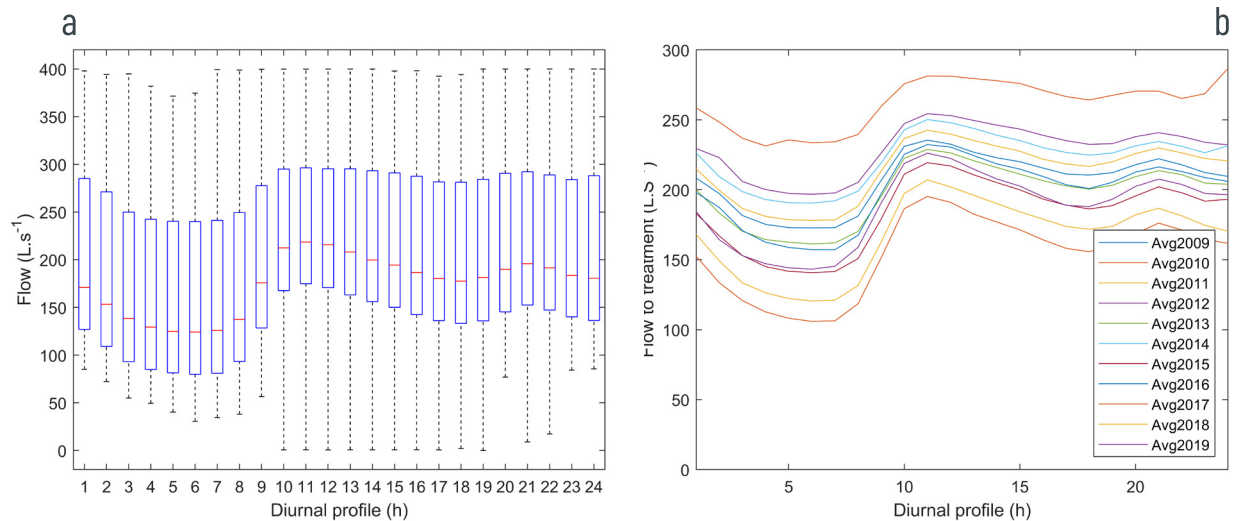


Fig. 4 Ten years of hourly flow data over a 24 h period aggregated into boxplots (a) and average flows by year (b).

Toward digital dynamic resilience of WRRF

The dynamics of digital systems have long been the interest of those working on solutions where real-world interfacing (sensors) is crucial for process control. Examples of this occur throughout robotic manufacturing and high-value fluids such as oil and gas. Unfortunately, being termed as a ‘waste’ rather than a ‘product’ places less importance on the value of the end product, resulting in less instrumentation (less consequential loss). Fortunately, for water companies, they generate data intensively from WRRF and processes. In decentralised rural locations, instruments are commonly used for compliance monitoring and are less likely to be used for real-time process control. However, larger centralised WRRF often combine monitoring of complicate with signals/data generated for process control. These larger WRRF processes have vast data silos spanning years or even decades. Much of this data generated for larger centralised WRRF holds clues to how dynamic stressors emerge and whether they generate process stress/resilience. Therefore, to avoid exhaustive iterations for modelling and simulation of scenarios, this data could be used as a timeseries to evaluate the dynamic resilience and generate knowledge of past and present events through empirical and mechanistic modelling. Modelling improves the context of events, and the data makes evaluating them relative to actual conditions. Over time it may be possible to make predictions on how future stressors may influence specific WRRF processes. A data-driven dynamic resilience philosophy therefore uses actual WRRF data and established modelling practices to compute the impact of a stressor, then process related stresses/resilience. This takes the focus from the intensive simulation of event based scenarios (stressors), to evaluating actual scenarios in the context WRRF instrument data.

Case study: dynamic resilience using 10 years of data from a WRRF in the south of the UK

In this section, 10 years of data has been used to 1) identify significant events through the evaluation of prominence and dominance, 2) extract a standard operating condition for an existing WRRF and 3) provide examples of dynamic resilience visualisations.

Evaluating the dominance and prominence of events under dynamic conditions

Events or stressors are typically characterised by their magnitude (the prominence of the variation). The most significant event magnitudes can be isolated then scaled for direct comparison. This can be done for both the stressor (cause) and process stresses/resilience (effect) which can be evaluated independently to isolate only the most severe, as shown in Fig. 5. When a significant event has been isolated using prominence, the event dominance can be estimated as the difference between the stressor exerted to the WRRF and the resultant process stresses/resilience. The difference in time between the stressor and process stress peaks allows estimation of the reaction time for applying interventions (maximum time to react). It is then possible to classify events as stressors and process stresses to estimate a reaction time for future events (i.e., the time between the stressor peak and the process stress occurring). Without event insight, it may not possible to learn from interventions applied to WRRF that reduce process-related stresses.

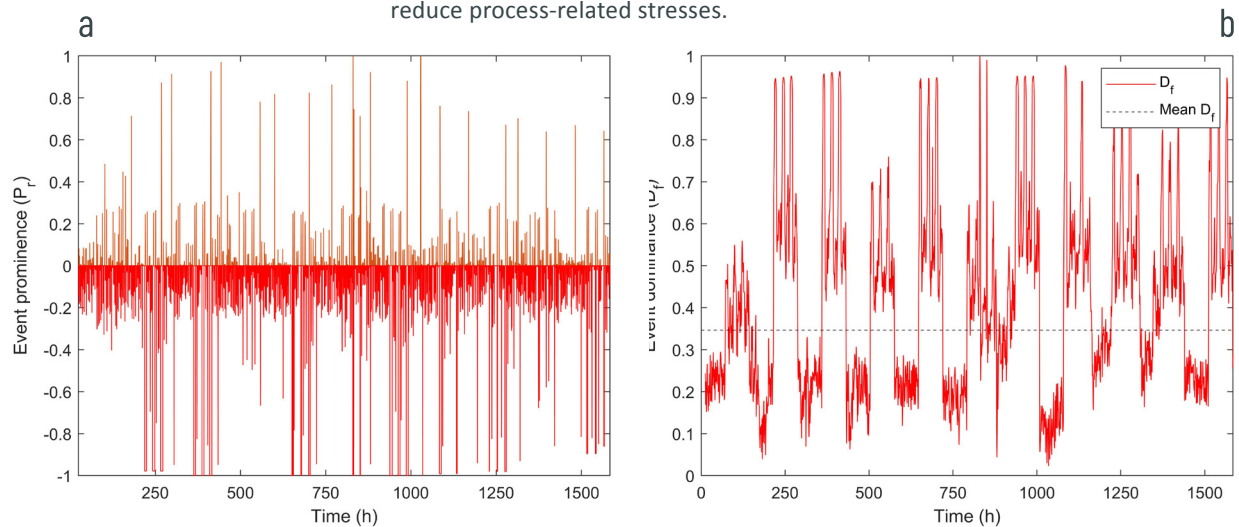


Fig. 5 Prominence (a) and dominance (b) of stressors and process stresses adapted from Holloway et al., 2021.

Examples of prominence are shown in Fig. 5a as time-based examples of stressor prominence (brown line) and process stresses prominence (red line). Significant events can be seen in Fig. 5a, when stressors are close to 1 and the resulting process stresses approach -1. The event dominance is shown in Fig. 5b (difference between the stressor and process stresses), allowing for isolation of events that have the most significant effect on process performance. Therefore, using prominence and dominance based analysis, stressor events can be isolated, then evaluated based on the effect the event has on the WRRF (process stress/resilience).

Failure as a consequence of normal operation

As much as we don't like to admit it, failure is a consequence of standard operation, originating from specific and operational changes or stressor influences. Therefore, as provided in the definition of resilience, failure also has a magnitude, with the extent of failure present over a scale. An example of this is failure to remove sludge from a system, which over time accumulates solids until a compliance breach occurs. This is far less significant, than a toxicity event that essentially kills off microbes in a biological system. Therefore, the extent of failure is crucial when evaluating resilience, meaning dynamic metrics then become scalable from a standard operating condition (where the process normally operates). Therefore, when we consider WRRF process failure, we must first consider the failure extent, and what constitutes a failure (*a failure of what and to what extent?*). For example, operational staff may consider the the color of the process fluids or visual tests to evaluate process conditions. These are empirical observations of indirect/internal stressors that prevent the process from functioning and are common. However, process scientists and engineers take more of a theoretical method of diagnostics, with failure defined as a compliance breach. Therefore, when considering events, it is essential to appreciate both empirical and theretical thought processes.

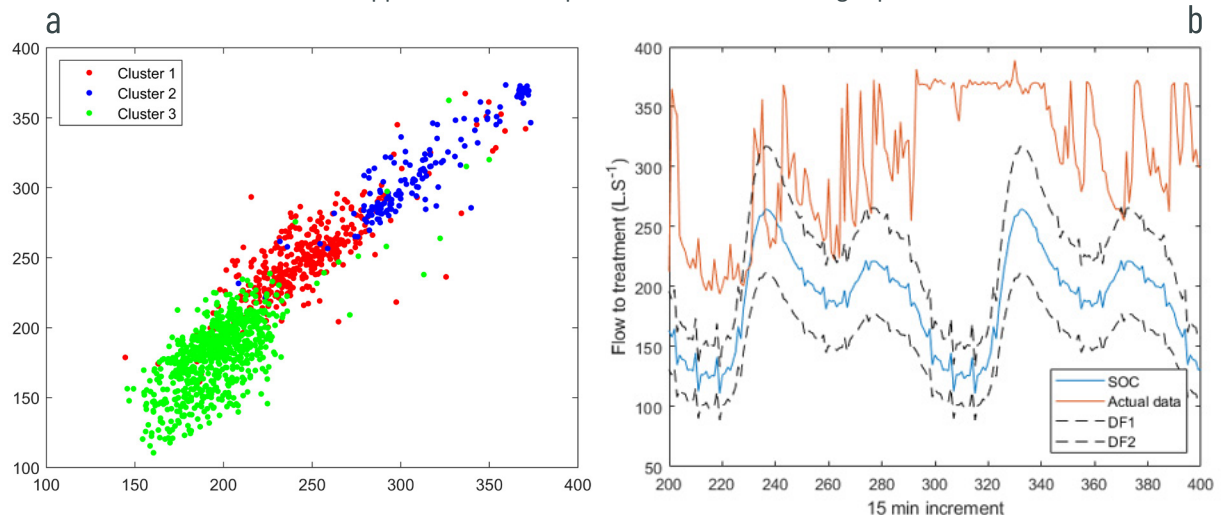


Fig. 6 Examples of clustering methods for the generation (a) and outputted SOC including degrees for freedom (b).

WRRF processes are subject to diurnal variation, which is also dynamic, but typical of standard operation for a specific wastewater catchment. Therefore, it differs from original WRRF process engineering design information, particularly when urban creep and populations in the wastewater catchment increase. The difference with dynamic resilience is that it takes the standard operation from actual operational data, rather than historial design information. This extracted condition is called the standard operating condition (SOC) relating specifically to the nuances of a catchment or WRRF. This can be done by using clustering methods to extract three flow conditions similar to that of Borzooei et al. (2020). The clustered outputs for a particular WRRF are shown in Fig. 6a, and the extracted SOC in Fig. 6b alongside actual time-based data. This SOC is important when considering WRRF that have been retrofitted with supplementary processes to increase WRRF capacity, which is common practice internationally. The extent of process failure is classified as the process stress index (PSI) and is anything outside a WRRF specific SOC.

The outputs of the clustering shown in Fig. 6 take an engineered resilience stance (Holling, 1996) and must be further elaborated to include a safety factor or degree of freedom to exclude normal variation (Fig. 6b). Also, outputs based on failure should consider the balance of compliance risk to operating costs, with evaluations based on the WRRF meeting permitted limits at the lowest operating cost. However, caution should be applied to a minimum operational cost approach so the process does not become unstable or vulnerable to changes resulting from external stressors. Therefore, evaluating the magnitude of variation (stressor) as the extent of failure allows failure prediction and numerous event classification possibilities based on process stress or resilience (i.e., dynamic resilience).

Communication of dynamic resilience

Visual communication is often overlooked, which is possibly why Corominas et al. (2018) found that only 16% of publications on transforming data into knowledge reference a commercially available product. Therefore, it is possible that there is a distinct gap between the evaluation of water resilience and how it is communicated to those operating and maintaining wastewater processes. The communication of resilience data, in the run up to a significant event can be challenging, particularly if there is no knowledge of past events and the associated interventions. Unfortunately, inadequate operational communication often comes as an incident investigation, such as the Longford gas plant explosion (Conlin and O'meara, 2006). This highlights the importance of linking resilience with complex modelled outputs in a communicable form for operational interpretation. It should also reflect the time-based dynamics of actual WRRF operating resilience.

To address this, the concept of dynamic resilience aims to incorporate time-based evaluations to visually communicate event severity to operational staff. Self-ordering windows (SOW) are used as a visualisation method for stressor and process stress/resilience observations. These SOW use a 48 hrs event window and, through transformation, plot the PSI as a contoured heat map. The SOW then becomes a significant event window based on its duration, prominence and dominance. In most cases, SOW represent a unique dynamic resilience fingerprint extracted from actual WRRF data, while keeping complex modelling practices out of sight (IWA ASM model series). The SOW principles also avoid having numerous number of iterations required for methods such as Monte-Carlo and other iterative simulations.

Examples of dynamic resilience are shown in Fig. 7 to demonstrate the impact of flow on heterotrophic biomass concentrations, where Fig. 7a shows the stressor and Fig. 7b the process stresses resulting from the stressor. The stressor in Fig. 7a shows concentrated zones at the highest flows and lowest concentrations and process stress at the highest concentration and middle of the flow range. The grey areas in each plot indicate zones of no data. Therefore, the concept of data richness is also crucial to SOW success, where inputs must reflect the time-based range and specific variation of the WRRF.

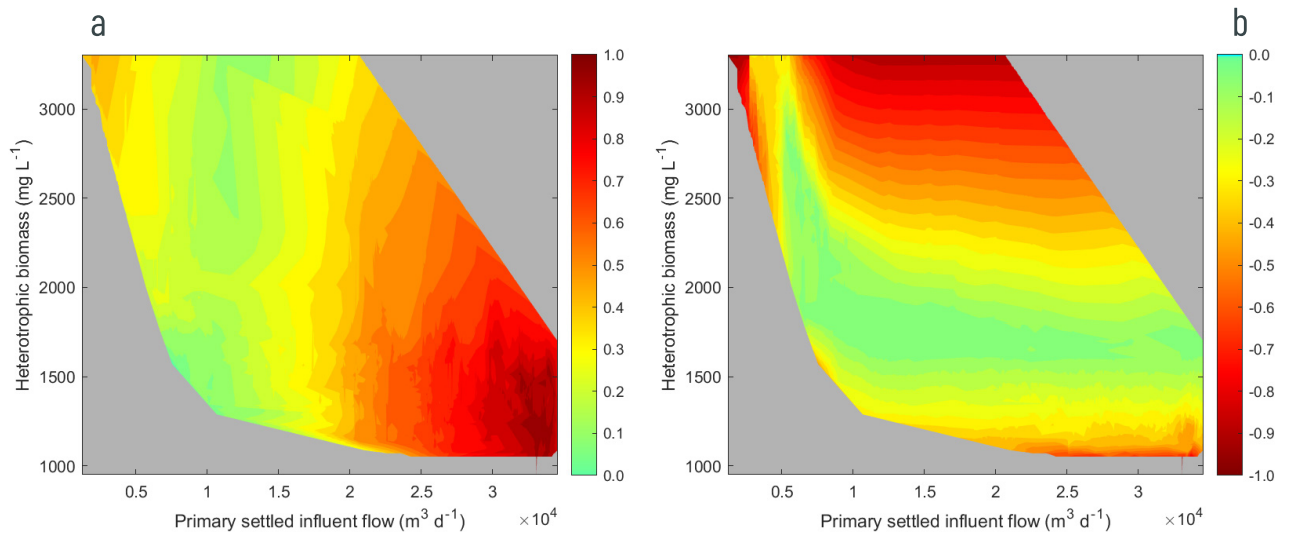


Fig. 7 Influence of a stressor and generated process stresses using the SOW approach for activated sludge.

The main challenge of dynamic resilience is the duration of the time-based window selected for evaluations. It can also be extremely difficult to predict when an event starts and ends, with characteristics varying depending on specific or multiple stressors. This will be crucial for the expansion of dynamic resilience to incorporate real time control (RTC) for live management of stressors and process stresses/resilience generated at the WRRF. An extension of that could be a traffic light system, as shown in Fig. 8, mapping the process stresses, but also communicating them for the application automated interventions.

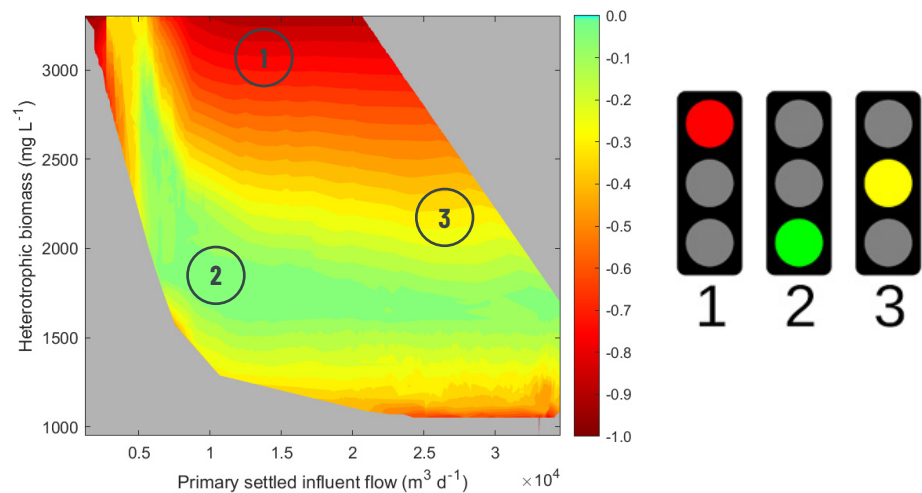


Fig. 8 Process stress analysis using the SOW principles, adapted from Holloway et al., 2021.

Summary of dynamic resilience methods

The dynamic resilience approach proposed in this white paper has demonstrated the possibility of using actual WRRF data to understand and communicate dynamic resilience. The methods presented used prominence and dominance to isolate significant events, then a macro data analysis approach to extract a dynamic SOC. Actual data points were used to scale system failure magnitude and compute the dynamic resilience of a specific WRRF as a SOW, which reflects specific process nuances in response to significant events. This includes the possibility of isolating novel events generated by climate or societal change. However, the main challenge for dynamic resilience is selecting a suitable time over which dynamic resilience is monitored, as this can dramatically influence SOW output and affect the classification of events.

Overall, the dynamic resilience methodology has provided a possible link between resilience, data-driven modelling and visualisations through time based contoured heat plots (SOW). It is hoped that these methods could eventually close gap between evaluating and modelling resilience and its communication to wastewater operators within water companies globally. However, the methods presented are limited to countries that 1) have the instrumentation installed in WRRF or networks and, 2) have the capacity and knowledge to maintain these instruments.

Reflection on dynamic resilience for an uncertain future

The future of the planet is reliant on how resilient the human race can be to changes in the climate and rapidly emerging stressors. As we face increasing uncertainty from political, social and environmental factors, water companies and government agencies are forced to manage the dynamics of resilience resulting from changes outside of their control. Although many theoretical methodologies of resilience have been proposed, a unified approach has not yet been developed to 1) satisfy the dynamics of resilience that occurs from an actual WRRF and 2) communicate outputs to operational and maintenance staff.

At the time of writing, the Russian invasion of Ukraine is causing significant political and economic instability. This, again, will likely generate novel stressors that result in process stresses in wastewater assets and infrastructure as transient populations exit Ukraine to neighbouring countries. These countries will now be subject to increased demand for clean water and increased capacity to treat additional wastewaters generated by those that have exited Ukraine. It is extremely likely (Pörtner et al., 2022) that we will continue to see the emergence of novel, rapidly emerging stressors, and if we continue on the same path, there is high confidence that their occurrences will increase.

It is also important to consider the factors that have contributed to stressors in recent history. Reflecting on the past three years, the following factors/stressors have emerged globally:

1. **February 2022:** IPCC WGII sixth assessment report predicts with high confidence global increases in inland flooding, flood and storm damage in coastal areas and damages to infrastructure (Pörtner et al., 2022).
2. **February 2022:** the Russian invasion of Ukraine caused the migration into neighbouring European countries.

3. **March 2020 to present:** the COVID-19 pandemic escalates, causing unprecedented damage to human health, global economies and freedom of movement (Ramos and Hynes, 2020).

The above emphasises the absolute need to understand the dynamic resilience of not just in assets and infrastructure but also due to societal change. Dynamic resilience has the premise of providing the means to understand the real-time adaptive capacity by monitoring stressors and process stresses/resilience directly from WRRF and associated processes (instruments). We must consider how existing instruments and data from these instruments can drive us toward Industry 4.0. Instrumentation combined with an understanding of dynamic resilience could allow us to understand and to adapt resilience in response to novel global events, while understanding where improvements can be made.

We already have many connected networks for intensive data exchange, along with large data silos (historical knowledge). Using these tools, it may be possible to access the real-time dynamic resilience of not just WRRF, but any interconnected infrastructure network. Therefore, the future of dynamic resilience and dynamic processes should embrace the possibility of improving resilience through digitally connected assets and infrastructure as the beating heart of the modern world (Fig. 9).

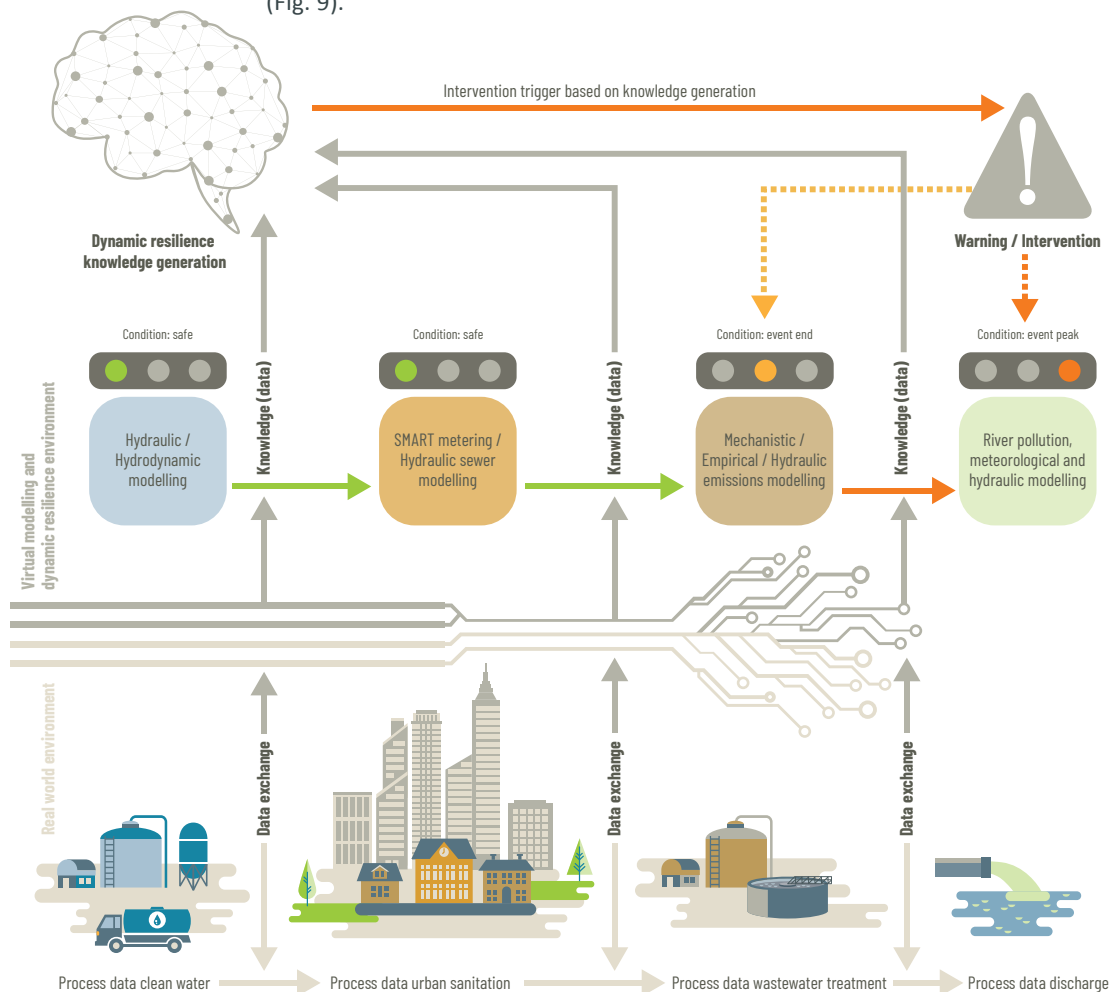


Fig. 9 Dynamic resilience for autonomy of the urban water cycle under the precept of Industry 4.0.

Additional resources

If this white paper has been of interest, please also watch our IWA MIA SG webinar on ‘*Modelling wastewater treatment resilience for improved decision making and resource recovery*’:

https://www.youtube.com/watch?v=jg8PPkP_zPc

If you have an interest in the research presented in this white paper, please complete our short survey (5 min):

<https://www.surveymonkey.co.uk/r/33FQ9BQ>

Acknowledgements

The lead author would like to personally thank the contributions made by Dr Matthew Wade and Dr Ben Martin. Also, the IWA for providing support in putting together the final version of this white paper.

References

Aguado, D., Blumensaat, F., Antonio Baeza, J., Villegz, K., Ruano Victoria, M., Samuelsson, O., Plana, Q., 2021. The value of meta-data for water resource recovery facilities. *Digit. Water* 15.

Ahmed, W., Angel, N., Edson, J., Bibby, K., Bivins, A., O’Brien, J.W., Choi, P.M., Kitajima, M., Simpson, S.L., Li, J., Tschärke, B., Verhagen, R., Smith, W.J.M., Zaugg, J., Dierens, L., Hugenholtz, P., Thomas, K. V, Mueller, J.F., 2020. First confirmed detection of SARS-CoV-2 in untreated wastewater in Australia: A proof of concept for the wastewater surveillance of COVID-19 in the community. *Sci. Total Environ.* 728, 138764. <https://doi.org/10.1016/j.scitotenv.2020.138764>

Borzooei, S., Miranda, G.H.B., Abolfathi, S., Scibilia, G., Meucci, L., Zanetti, M.C., 2020. Application of unsupervised learning and process simulation for energy optimization of a WWTP under various weather conditions. *Water Sci. Technol.* 81, 1541–1551. <https://doi.org/10.2166/wst.2020.220>

Butler, D., Farmani, R., Fu, G., Ward, S., Diao, K., Astaraie-Imani, M., 2014. A new approach to urban water management: safe and sure. *Procedia Eng.* 89, 347–354. <https://doi.org/10.1016/j.proeng.2014.11.198>

Conlin, H., O’meara, J., 2006. Assessing Longford Gas Plant 1 Staffing Arrangements. *Process Saf. Environ. Prot.* 84, 10–20. <https://doi.org/10.1205/psep.04245>

Corominas, L., Garrido-Baserba, M., Villegz, K., Olsson, G., Cortés, U., Poch, M., 2018. Transforming data into knowledge for improved wastewater treatment operation: a critical review of techniques. *Environ. Model. Softw.* 106, 89–103. <https://doi.org/10.1016/j.envsoft.2017.11.023>

Crits-Christoph, A., Kantor, R.S., Olm, M.R., Whitney, O.N., Al-Shayeb, B., Lou, Y.C., Flamholz, A., Kennedy, L.C., Greenwald, H., Hinkle, A., Hetzel, J., Spitzer, S., Koble, J., Tan, A., Hyde, F., Schroth, G., Kuersten, S., Banfield, J.F., Nelson, K.L., Pettigrew, M.M., 2021. Genome Sequencing of Sewage Detects Regionally Prevalent SARS-CoV-2 Variants. *MBio* 12, e02703-20. <https://doi.org/10.1128/mBio.02703-20>

Daigger, G.T., 2009. Evolving urban water and residuals management paradigms: water reclamation and reuse, decentralization, and resource recovery. *Water Environ. Res. a Res. Publ. Water Environ. Fed.* 81, 809–823. <https://doi.org/10.2175/106143009x425898>

Fischer, E.M., Sedláček, J., Hawkins, E., Knutti, R., 2014. Models agree on forced response pattern of precipitation and temperature extremes. *Geophys. Res. Lett.* 41, 8554–8562. <https://doi.org/10.1002/2014GL062018>

Grievson, O., 2020. Digital water: the role of instrumentation in digital transformation. *Digit. Water* 19.

Guest, J.S., Skerlos, S.J., Barnard, J.L., Beck, M.B., Daigger, G.T., Hilger, H., Jackson, S.J., Karvazy, K., Kelly, L., Macpherson, L., Mihelcic, J.R., Pramanik, A., Raskin, L., Van Loosdrecht, M.C.M., Yeh, D., Love, N.G., 2009. A New Planning and Design Paradigm to Achieve Sustainable Resource Recovery from Wastewater. *Environ. Sci. & Technol.* 43, 6126–6130. <https://doi.org/10.1021/es9010515>

Gwenzi, W., 2022. Wastewater, waste, and water-based epidemiology (WWW-BE): A novel hypothesis and decision-support tool to unravel COVID-19 in low-income settings? *Sci. Total Environ.* 806, 150680. <https://doi.org/10.1016/j.scitotenv.2021.150680>

Harper, D., 2019. Online Etymology Dictionary: Resilience [WWW Document]. Web Page. URL <https://www.etymonline.com/word/resilience> (accessed 11.17.19).

Holling, C.S., 1996. Engineering resilience versus ecological resilience. *Eng. within Ecol. Constraints* 224. <https://doi.org/10.17226/4919>

Holling, C.S., 1973. *Resilience and Stability of Ecological Systems* 4, 4050-. <https://doi.org/10.1146/annurev.es.04.110173.000245>

Holloway, T. G., Jeppsson, U., Fu, G., Secu, S., Molinos-Senante, M., 2021. Modelling wastewater treatment resilience for improved decision making and resource recovery. IWA.

Holloway, T G., Williams, J.B., Ouelhadj, D., Yang, G., 2021. Dynamic resilience for biological wastewater treatment processes: Interpreting data for process management and the potential for knowledge discovery. *J. Water Process Eng.* 42, 102170. <https://doi.org/10.1016/j.jwpe.2021.102170>

Juan-García, P., Butler, D., Comas, J., Darch, G., Sweetapple, C., Thornton, A., Corominas, L., 2017. Resilience theory incorporated into urban wastewater systems management. State of the art. *Water Res.* 115, 149–161. <https://doi.org/10.1016/j.watres.2017.02.047>

Kehrein, P., van Loosdrecht, M., Osseweijer, P., Garfí, M., Dewulf, J., Posada, J., 2020. A critical review of resource recovery from municipal wastewater treatment plants – market supply potentials, technologies and bottlenecks. *Environ. Sci. Water Res. Technol.* 6, 877–910. <https://doi.org/10.1039/C9EW00905A>

Larsen, D.A., Green, H., Collins, M.B., Kmush, B.L., 2021. Wastewater monitoring, surveillance and epidemiology: a review of terminology for a common understanding. *FEMS Microbes* 2. <https://doi.org/10.1093/femsmc/xtab011>

Mao, K., Zhang, K., Du, W., Ali, W., Feng, X., Zhang, H., 2020. The potential of wastewater-based epidemiology as surveillance and early warning of infectious disease outbreaks. *Curr. Opin. Environ. Sci. Heal.* 17, 1–7. <https://doi.org/10.1016/j.coesh.2020.04.006>

Mugume, S.N., Gomez, D.E., Fu, Guangtao, Farmani, R., Butler, D., 2015. A global analysis approach for investigating structural resilience in urban drainage systems. *Water Res.* 81, 15–26. <https://doi.org/10.1016/j.watres.2015.05.030>

NASA, N.A. and S.A., 2016. Scientific consensus: Earth's climate is warming [WWW Document]. Web Page. URL <https://climate.nasa.gov/scientific-consensus>

Newhart, K.B., Holloway, R.W., Hering, A.S., Cath, T.Y., 2019. Data-driven performance analyses of wastewater treatment plants: a review. *Water Res.* 157, 498–513. <https://doi.org/10.1016/j.watres.2019.03.030>

Ofwat, 2019. Ofwat: PR19 Initial assessment of business plans – key documents [WWW Document]. Web Resour. page. URL <https://www.ofwat.gov.uk/investor/pr19/> (accessed 6.18.19).

Pörtner, H.O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Minterbeck, A., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., Rama, B., 2022. IPCC, 2022: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK.

Ramos, G., Hynes, W., 2020. A systematic resilience approach to dealing with COVID-19 and future shocks.

Sweetapple, C., Fu, G., Farmani, R., Butler, D., 2022a. General resilience: Conceptual formulation and quantitative assessment for intervention development in the urban wastewater system. *Water Res.* 211, 118108. <https://doi.org/10.1016/j.watres.2022.118108>

Sweetapple, C., Melville-Shreeve, P., Chen, A.S., Grimsley, J.M.S., Bunce, J.T., Gaze, W., Fielding, S., Wade, M.J., 2022b. Building knowledge of university campus population dynamics to enhance near-to-source sewage surveillance for SARS-CoV-2 detection. *Sci. Total Environ.* 806, 150406. <https://doi.org/10.1016/j.scitotenv.2021.150406>

Tulchinsky, T.H., 2018. John Snow, Cholera, the Broad Street Pump; Waterborne Diseases Then and Now. *Case Stud. Public Heal.* <https://doi.org/10.1016/B978-0-12-804571-8.00017-2>

Wade, M.J., Lo Jacomo, A., Armenise, E., Brown, M.R., Bunce, J.T., Cameron, G.J., Fang, Z., Farkas, K., Gilpin, D.F., Graham, D.W., Grimsley, J.M.S., Hart, A., Hoffmann, T., Jackson, K.J., Jones, D.L., Lilley, C.J., McGrath, J.W., McKinley, J.M., McSparron, C., Nejad, B.F., Morvan, M., Quintela-Baluja, M., Roberts, A.M.I., Singer, A.C., Souque, C., Speight, V.L., Sweetapple, C., Walker, D., Watts, G., Weightman, A., Kasprzyk-Hordern, B., 2022. Understanding and managing uncertainty and variability for wastewater monitoring beyond the pandemic: Lessons learned from the United Kingdom national COVID-19 surveillance programmes. *J. Hazard. Mater.* 424, 127456. <https://doi.org/10.1016/j.jhazmat.2021.127456>

Walker, B., Holling, C.S., Carpenter, S.R., Kinzig, A., 2004. Resilience, Adaptability and Transformability in Social– ecological Systems. *Ecol. Soc.* 9, 5.

Wu, J., Wang, Z., Lin, Y., Zhang, L., Chen, J., Li, P., Liu, W., Wang, Y., Yao, C., Yang, K., 2021. Technical framework for wastewater-based epidemiology of SARS-CoV-2. *Sci. Total Environ.* 791, 148271. <https://doi.org/10.1016/j.scitotenv.2021.148271>

ABOUT THE INTERNATIONAL WATER ASSOCIATION

The International Water Association (IWA) is the leading network and global knowledge hub for water professionals, and anyone committed to the future of water. IWA, which is a non-profit organisation, has a legacy of over 70 years.

IWA connects water professionals in over 130 countries to find solutions to global water challenges as part of a broader sustainability agenda. IWA connects scientists with professionals and communities so that pioneering research provides sustainable solutions.

In addition, the association promotes and supports technological innovation and best practices through international frameworks and standards. Through projects, events, and publications, IWA engages with its members to stimulate innovative ideas and content in support of IWA's vision of a water-wise world.



INTERNATIONAL WATER ASSOCIATION

Export Building, 1st Floor
1 Clove Crescent
London E14 2BA
United Kingdom
Tel: +44 207 654 5500
Fax: +44 207 654 5555
E-mail: water@iwahq.org

Company registered in England No.3597005
Registered Charity in England No.1076690

www.iwa-network.org