

Forward-Looking Roadmaps for Long-Term Continuous Water Quality Monitoring: Bottlenecks, Innovations, and Prospects in a Critical Review

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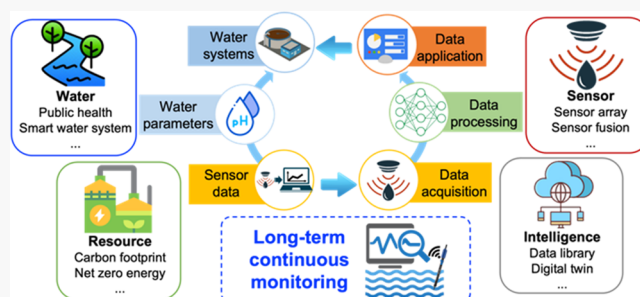
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ABSTRACT: Long-term continuous monitoring (LTCM) of water quality can bring far-reaching influences on water ecosystems by providing spatiotemporal data sets of diverse parameters and enabling operation of water and wastewater treatment processes in an energy-saving and cost-effective manner. However, current water monitoring technologies are deficient for long-term accuracy in data collection and processing capability. Inadequate LTCM data impedes water quality assessment and hinders the stakeholders and decision makers from foreseeing emerging problems and executing efficient control methodologies. To tackle this challenge, this review provides a forward-looking roadmap highlighting vital innovations toward LTCM, and elaborates on the impacts of LTCM through a three-hierarchy perspective: data, parameters, and systems. First, we demonstrate the critical needs and challenges of LTCM in natural resource water, drinking water, and wastewater systems, and differentiate LTCM from existing short-term and discrete monitoring techniques. We then elucidate three steps to achieve LTCM in water systems, consisting of data acquisition (water sensors), data processing (machine learning algorithms), and data application (with modeling and process control as two examples). Finally, we explore future opportunities of LTCM in four key domains, water, energy, sensing, and data, and underscore strategies to transfer scientific discoveries to general end-users.

KEYWORDS: water system, sensors, long-term continuous monitoring, data processing, process control, emerging contaminants



1. INTRODUCTION

Pursuing sustainable solutions for water scarcity, ensuring water quality and availability, protecting human and ecosystem health, and producing renewable energy have become top priorities for water and wastewater treatment facilities.^{1–3} Stakeholders from academia, industry and government have put forth concerted efforts to develop innovative technologies (e.g., anaerobic digestion (AD),⁴ membrane bioreactor (MBR),⁵ and reverse osmosis (RO)⁶) with the aims of maintaining high water quality and recovering value-added sources (e.g., carbon,⁷ nitrogen,⁸ metals,⁹ biogas,¹⁰ and clean water¹¹). However, the current understanding of process dynamics (e.g., microbial activities, parameter interactions, and reaction kinetics) is still limited, posing hindrances for implementation of state-of-the-art technologies. To address these challenges, thorough knowledge of dynamic water systems is acquired to predict and diagnose acute shocks and/or chronic fluctuations, advance system resilience, augment treatment efficiency, reduce carbon footprint, and maximize resource values. Fulfilling this initiative heavily relies

on trustable water sensors to monitor multiplex physicochemical and biochemical reactions occurring in water and wastewater streams, a spatiotemporal data processing capability to promptly process numerous types of data collected at varying time frames, and a hyperspectral data application to interpret and apply sensor data into diverse water systems.^{12–14}

Water monitoring approaches can be divided into four temporal scales based on the sensing capability, monitoring media, and target analyte, namely, short-term discrete monitoring (STDM; Sensors are deployed in water solutions at the time scale of minutes or hours, in which sensor data are obtained at low temporal resolution (time interval >1 h).),

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Table 1. Comparison of Four Water Monitoring Strategies (STDM, STCM, LTDM, and LTCM) Based on the Temporal Scale

Monitoring patterns	STDM	STCM	LTDM	LTCM
Temporal resolution	>1 h	<1 h	>1 h	<1 h
Data continuity	Discrete data	Continuous data	Discrete data	Continuous data
Monitoring duration	<hrs	<hrs	>days	>days
Capability for maintenance-free automatic monitoring	Low	Low	Ordinary	High
Capability for detection of abnormal occurrences	Low	Low	Ordinary	High
Typical water systems targeted	NRW, DW/WW physicochemical units	NRW, DW/WW physicochemical units	NRW, DW/WW physicochemical units	NRW, DWDSs, DW/WW physicochemical/biochemical units
Typical parameters targeted	Turbidity, bacteria count	DO, chlorine	Temperature, flow rate, pH	Nitrogen, heavy metals, ECs
Requirement of sensor performance	Low	Medium	Medium	High
Requirement for data acquisition/collection/precession	Low	Medium	Medium	High
Typical types of sensors	Voltammetric/optical/biosensors	Amperometric/potentiometric/biosensors	Voltammetric/conductimetric/optical sensors	Amperometric/potentiometric/optical sensors

short-term continuous monitoring (STCM; Sensors are deployed at the same time scale as STDM, but sensor data are obtained at high temporal resolution (time interval <1 h).), long-term discrete monitoring (LTDM; Sensors are deployed intermittently into the water solution at the time scale of days, weeks or even months, during which data are obtained at low temporal resolution (time interval >1 h) and human power is needed to deploy and replace sensors over time.), and long-term continuous monitoring (LTCM; Sensors are deployed at the same time scale as LTDM, but with minimal requirement of maintenance, displacement or replacement. Sensor data are obtained at high temporal resolution (time interval <1 h or even in minutes)) (Table 1). Among these four monitoring approaches, LTCM possesses distinct advantages by providing real-time, *in situ* and high-fidelity information essential for tracking transient variations of water parameters (compared to STDM and STCM), elucidating panoramic water dynamics with minimal requirement of manual intervene (compared to LTDM), and implementing spatiotemporal data sets to address data sparsity or deviation through fault detection and self-calibration.

The last two decades have witnessed numerous applications of water sensors in natural resource water (NRW), drinking water (DW), and wastewater (WW), as demonstrated by an expeditious growth in the number of publications (4157) on water quality monitoring between 2000 and 2020 (Figure 1a). However, the publications related with long-term monitoring (216), continuous monitoring (257), and LTCM (113, among which 79 papers were limited to lab tests) in water systems/processes are fairly inadequate, compared with 3941 papers on short-term monitoring (Figure 1b). Furthermore, existing reviews related with sensing technology and water quality engineering fail to consider the impacts of LTCM applications in water systems. Specifically, the reviews of sensor materials/data processing innovations have mainly focused on STDM and STCM,^{15–19} due to the underperformance of water sensors in long-term accuracy and durability caused by various reasons such as biofouling,²⁰ aqueous layer formation,²¹ sensor material depletion,²² interference particles/ion,²³ inadequate data collection/interpretation,²⁴ and labor-intensive and technical-demanding maintenance.²⁵ Additionally, the reviews on water pollutants (e.g., nutrients such as nitrogen and phosphorus,^{26–31} heavy metals such as lead and chromium,^{32–36} and emerging contaminants (ECs) such as micro-

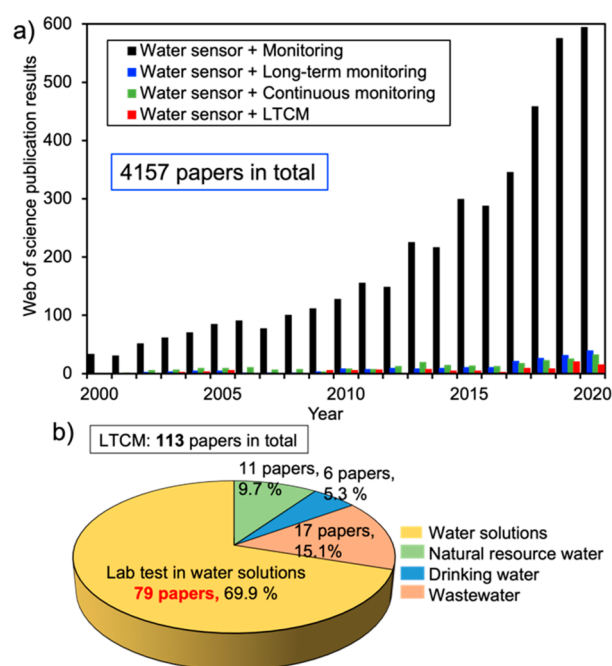


Figure 1. (a) The number of articles on water sensor application per year since 2000. The articles were identified using Web of Knowledge search queries with the keyword “water sensor” combined with the categories of water systems (NRW, DW, and WW). (b) The studies of LTCM in each type of water systems.

plastics (MPs)^{37–48} and pesticides^{49–57}, water systems (e.g., AD,^{58–61} bioelectrochemical systems (BES),^{62–66} and DW distribution networks^{67–70}), and control strategies (e.g., proportional-integral-derivative (PID) control^{71–73}) have been limited to environmental applications based on either short-term or discrete sensing data without recognizing the new viewpoint that LTCM can bring. To date, the critical roadblocks of LTCM in water systems have not been effectively addressed.

We contend there is a critical need to conceptualize LTCM and its implementations in water systems. This review focuses on bridging the gap between the fundamental knowledge of sensors and the application of LTCM techniques by illustrating the roles and importance of LTCM at three layers (sensor data, water parameters, and system level) and explicating the

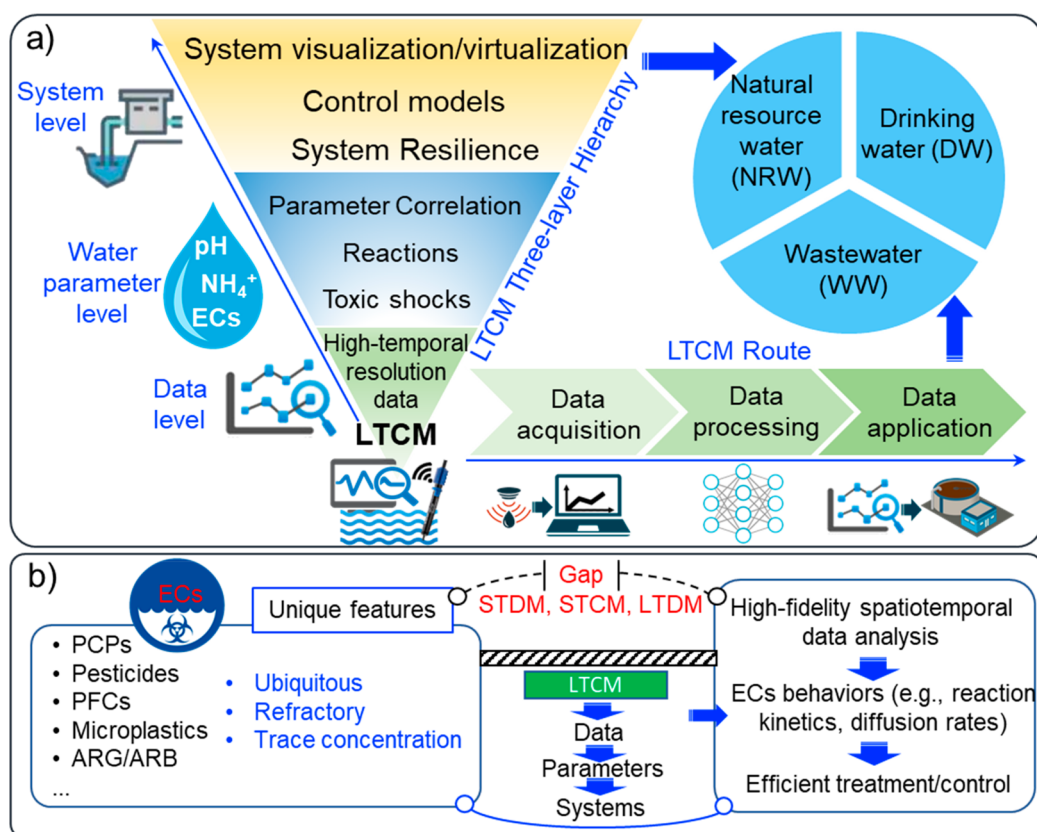


Figure 2. Comprehensive scheme demonstrating the critical role of LTCM for water systems. (a) The 3-layer hierarchy perspective (sensor data, water parameters, and system level) of LTCM and the complete route of LTCM. (b) EC as an example illustrating the advantages of LTCM over traditional short-term and discrete monitoring.

longitudinal route of LTCM consisting of sensor data generation, data processing, and data application (Figure 2a). Specifically, we first explore the current state and challenges of LTCM in three major water systems including NRW, DW, and WW, as they are the principal aquatic environments for the fate/transfer of contaminants through complicated physiochemical and biochemical reactions, and have high impacts on numerous key element cycles, human-nature interactions, and climate change. Afterward, we demonstrate the state-of-the-art water sensing technologies for data acquisition of LTCM and elaborate the capability and limitation of each type of sensing technology. We then present the LTCM data collection and data processing through sensor networks and machine learning (ML) algorithms. Subsequently, we interpret the LTCM data application with water system modeling and process control as two distinct examples. Finally, we unveil the outlook of LTCM in four major domains: water, energy, sensors, and data science. Based on the review findings, we elucidate the complete route of LTCM from initial data acquisition to final data application, differentiate LTCM from traditional monitoring strategies (STDM, STCM, and LTDM), and present future perspectives such as deep learning (DL) sensor fusion, digital water infrastructure, and data-driven carbon footprint modeling.

2. CRITICAL NEEDS OF LTCM IN WATER SYSTEMS

In this section we demonstrate the critical needs and challenges of LTCM in NRW, DW, and WW systems. Because of the difficulties of LTCM deployment (e.g., seasonal variations in NRW, stringent sensor safety requirements in

DW, and high solid contents and microbial activities in WW), current monitoring strategies still depend on conventional monitoring methods including STDM, STCM, and LTDM to predict parameter fluctuation and formulate control strategies. We identify the appropriate LTCM approaches through a three-layer hierarchy: sensor data, water parameters, and system level as well as explore the possibility of incorporating the data obtained from different time-framed regimes (e.g., short-term/long-term and discrete/continuous patterns) to enrich the information output without sacrificing the accuracy.

2.1. LTCM in NRW: Critical Demands and Challenges.

Enactment of stringent water quality regulations (e.g., arsenic: 10 ppb in wells⁷⁴) of NRW becomes imperative due to the deterioration of the water environment from natural changes (e.g., heavy metal desorption from soil to groundwater⁷⁵), human impacts (e.g., discharge of ECs with long-distance transport pathways⁷⁶), and their combinations (e.g., landfill leaching⁷⁷). *In situ* treatment techniques have been deployed to remove contaminants in NRW. For example, 45% of polyfluoroalkyl substances (PFASs) were degraded by *Phanaerochete chrysosporium* within 35 days in groundwater.⁷⁸ However, existing conceptual and empirically based hydrological models such as Soil and Water Assessment Tool models⁷⁹ are validated only with the data obtained from short-term and/or long-term discrete monitoring (e.g., temperature sensing interval: one point/day⁸⁰), posing difficulties for innovating treatment processes in NRW systems featured with varying temporal and spatial scales.⁸¹

At the data level, LTCM in NRW presents long-lasting and affluent patterns of water quality states and fluxes that aids data

aggregation and solves data sparsity. At the water parameter level, LTCM can elucidate the correlation among different water parameters in NRW undergoing seasonal changes and facilitate the identification of solutions for emerging problems. For example, LTCM can provide year-around information for determining carbon/nitrogen dynamics and concentration gradients in different types of NRW (e.g., groundwater, rivers, and lakes), and developing data-driven models to characterize the carbon footprint.⁸² Moreover, the high-dimensional data sets obtained from LTCM, LTDM, STCM, and STDM can be combined through data fusion, in which a metadata schema can be generated to profile the physicochemical and biochemical status and illustrate the uncertainties caused by human–nature interactions in NRW systems.⁸³ For example, a lab-on-chip analyzer was used to illustrate phosphate variations at a hourly sensing interval and achieve a linear quantification for 60 days in coastal water.⁸⁴ In addition, state-of-the-art models built from personalized data sets generated from LTCM can be adapted to water dynamics for better prediction of water parameters (Figure 2a). ML models based on 30-year remote sensing data have been applied to predict the dissolved oxygen (DO) concentration in the Lake Huron (Michigan, U.S.) with the R^2 value of 0.91.⁸⁵ However, the long-term accuracy of the sensors deployed in NRW is severely undermined by seasonal changes of water characteristics (e.g., temperature fluctuations affect the potentiometric sensor readings⁸⁶), and the continuous accuracy of these sensors is impaired by unpredictable incidences in NRW such as alterations of salinity/water flux under weather variation and human activity associated disruptions.^{87,88}

2.2. LTCM in DW: Critical Demands and Challenges.

Water quality in DW distribution systems (DWDSs) can be deteriorated by pathogen regrowth (e.g., *Campylobacter* spp.⁸⁹ and SARS-CoV-2⁹⁰), formation of extracellular polymeric substances (EPS) on the pipeline, and pipeline corrosion. In addition, DW quality also suffers from EC pollution (e.g., bisphenol A⁹¹) via migration of contaminated groundwater plumes from point sources⁹² and/or air emission followed by deposition and soil/liquid desorption.⁹³ State-of-the-art treatment processes such as nanofiltration (NF) (98% removal efficiency of PFASs⁹⁴) and metallic microfiltration (MF) (99% removal efficiency of *Cryptosporidium parvum*⁹⁵) have been used in DW treatment plants (DWTPs) to remove low concentrated ECs (e.g., perfluorooctanoic acid (PFOA) < 1 $\mu\text{g/L}$ ⁹⁶). Recently, water microgrids capable of minimizing environmental impacts by controlling water distribution in DWDSs have started to gain a great deal of attention for improving the DW quality.⁹⁷ However, developing water microgrid models (e.g., mixed integer nonlinear programming model) and visualizing DWDSs require a robust monitoring capability for data communication between operation nodes and command centers, which is limited by current short-term and discrete monitoring techniques.⁹⁸

LTCM can capture erratic contaminant shocks occurring in DW pipelines and treatment units by presenting high temporal resolution data. Consequently, DWTPs can expedite implementing appropriate strategies and effective responses in a timely manner at the water parameter level (e.g., dosage control based on the sensor data), and finally improve water treatment strategies and system control (Figure 2a). For example, dynamic biofilm-based stainless steel electrochemical sensors have been applied to guide the disinfectant dosage in DWTPs on a real-time basis.⁹⁹ Other than discrete data at a

low spatiotemporal resolution, LTCM using Supervisory Control and Data Acquisition (SCADA) for DWDSs can provide high-dimensional data-driven detection of cyberattacks to improve resilience and safety in water microgrids.¹⁰⁰ However, the leaching of toxic chemicals (e.g., plasticizers in some types of potentiometric sensors¹⁰¹) to the DW can deteriorate the water quality, leading to the strict limitation of the DW sensors to the reagent-free or reagent release-free (e.g., using a paper-based sensor embedded in a 3D printing device¹⁰²) to prevent potential contamination caused by these sensors during LTCM. Another challenge for continuous monitoring comes from the difficulties of optimizing sensor deployment locations to promptly capture the episodic and nonperiodic occurrences (e.g., pipeline corrosion, biofilm formation, and transient shocks) in the intricate DW networks.

2.3. LTCM in WW: Critical Demands and Challenges.

WW contains abundant substances such as nitrogen and carbon that make it a valuable renewable resource. Ensuring WW effluent quality while achieving resource recovery have been energy intensive due to the limited understanding of multiplex physiochemical and biochemical reactions, dynamic flow patterns, and complicated interactions between contaminants and microorganisms in WW treatment processes. Innovations in controller algorithms are promising to formulate state-of-the-art treatment technologies in a cost-effective and energy-efficient way. For example, phosphorus recovery was increased from 13.7% to 29.6% in biological nutrient removal (BNR) systems by using a fuzzy logic control.¹⁰³ However, numerous parameters (e.g., DO, inorganic/organic contaminants, suspend solid, and pathogens) are associated with each other, creating intertwined relationships that could not be deciphered using existing short-term and discrete temporal data.

Implementation of LTCM could provide effective solutions for energy-intensive WW treatment processes by monitoring variations of water parameters in a real time *in situ* mode and tracking their long-term patterns from the data level to the water parameter level. Additionally, at the system level LTCM can establish high-fidelity parameter inputs and outputs for control models and achieve system visualization and virtualization toward enhanced resilience (Figure 2a). For example, LTCM of EPS using cation exchange resin sensors could enhance resource recovery and water reuse in a zero-waste discharge aerobic granular sludge reactor by controlling the organic loading rate.¹⁰⁴ Furthermore, using electrochemical sensors as the LTCM and LTDM devices to quantify nitrogen and DO can accurately profile the water quality variations and reaction kinetics in BNR reactors such as photosequencing batch reactors¹⁰⁵ and integrated vertical membrane bioreactors.¹⁰⁶ However, the main challenge for long-term monitoring in WW is the rapid deterioration of sensor performance,¹⁰⁷ while continuous monitoring is impaired by numerous interference factors in complex WW mediums (e.g., high biomass content, vigorous mixing, and pH fluctuation^{4,108}).

3. CURRENT STATE AND CHALLENGE OF SENSOR DEVELOPMENT FOR DATA ACQUISITION IN LTCM

Data acquisition using appropriate water sensors is the fundamental step to achieve LTCM. In this section, we provide an overview of the state-of-the-art sensor development, including electrochemical sensors, optical sensors, and biosensors along with their possible applications. Especially, we discuss the challenges of ECs (e.g., PFCs and MPs)

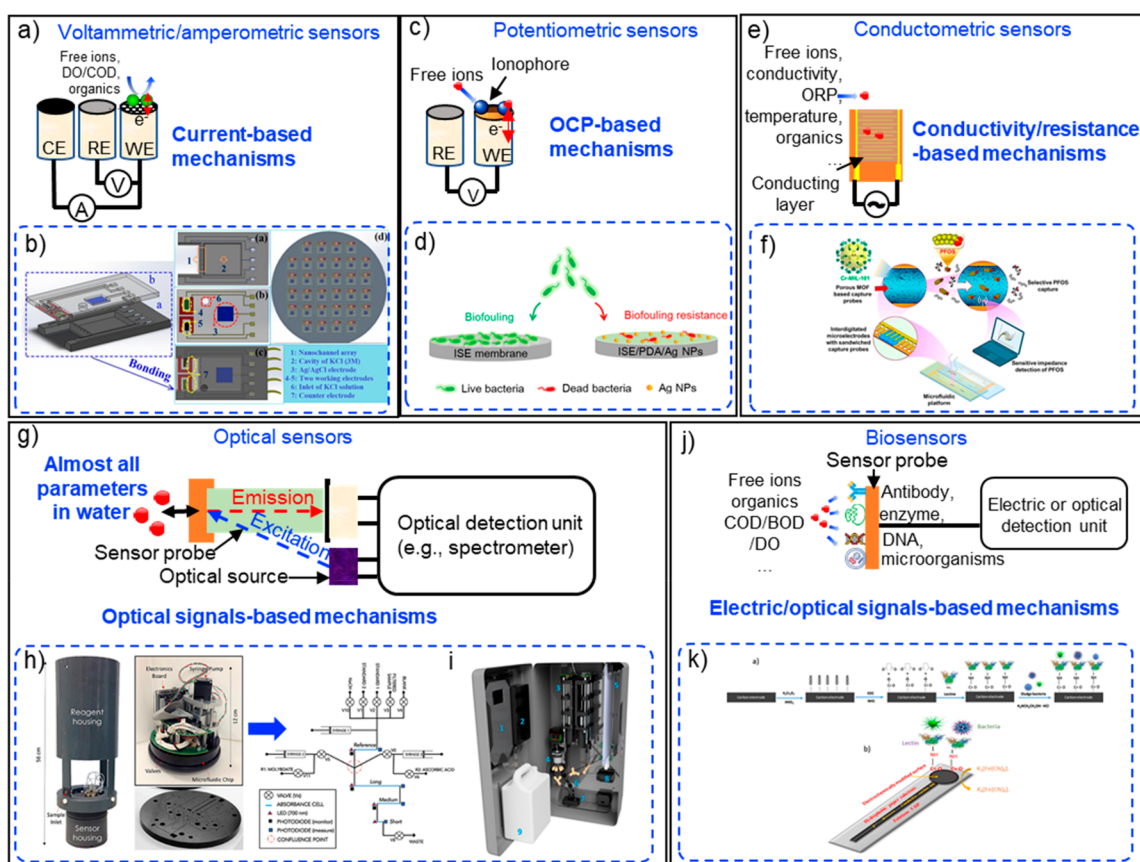


Figure 3. State-of-the-art water sensor development for LTCM. (a) The mechanism of voltammetric/amperometric sensors. (b) Silicon-based modified voltammetric sensor to improve durability.¹¹⁶ (c) Sensing mechanism of potentiometric sensors. (d) Silver nanoparticles modified potentiometric sensors to improve antifouling capability.¹²⁸ (e) Sensing mechanism of conductometric sensors. (f) MOF-based conductometric sensors for perfluorooctanesulfonic acid (PFOS) detection.¹³⁵ (g) Sensing mechanism if optical sensors. (h) Lab-on-chip optical sensor for long-term *in situ* monitoring of phosphate.¹⁹⁵ (i) Fully automated ion chromatography system for *in situ* analysis of nitrite and nitrate.¹⁹⁴ (j) Sensing mechanism of biosensors. (k) Impedimetric paper-based biosensor for bacteria detection.²⁰²

monitoring in water systems. We differentiate the sensors for STD, STCM, LTDM, and LTCM as well as identify the distinct features of each type of sensors in various monitoring scenarios.

3.1. Electrochemical Sensors for LTCM. Electrochemical sensors measure the concentration of target analytes in a water solution by quantifying electrical signals (e.g., current, potential, or charge).¹⁰⁹ According to sensing mechanisms, electrochemical principles, and electronic outputs, electrochemical sensors discussed here are divided into three categories: voltammetric/amperometric sensors, potentiometric sensors, and conductometric sensors.¹¹⁰

Voltammetric/Amperometric Sensors. Voltammetric/amperometric sensors quantify the analytes by measuring the current generated from reduction/oxidation reactions on the electrode surface under varying (voltammetry) or constant (amperometry) potentials.^{111,112} The current observed at different electron transfer rates is directly associated with the analyte concentration (Figure 3a). With proper storage procedures (e.g., two-month storage in darkness for indoaniline-derivative type pH voltammetric sensors¹¹³), voltammetric/amperometric sensors can detect chemical oxygen demand (COD), NO_2^- and ClO^- with low detection limits (ppm and ppb levels) for 6 to 90 days in water systems (Table 2). Additionally, amperometric sensors can quantify viable microbes by continuously monitoring dissolved oxygen

coupled with principal component analysis.¹¹⁴ These sensors can also be modified using nanoporous Au,¹¹⁵ a Si-glass structured sensor chip,¹¹⁶ and a nanostructured ion imprinted polymer¹¹⁷ to enhance the responding capability for the oxidation/reduction processes occurring on the electrode surface (Figure 3b). One critical challenge of voltammetric/amperometric sensors for long-term application is the formation of passive compounds on the working electrode surface (e.g., platinum oxide on Pt-based electrodes) that causes measurement drift and finally shortens the lifespan.^{118,119} Moreover, the current value (mA) obtained by voltammetry/amperometry techniques can be drifted by ion interference¹²⁰ and temperature variations,¹²¹ which inhibits their applications for continuous monitoring in WW containing high concentration of interfering ions (e.g., chloride $>0.5 \text{ M}$ ¹²²) and featuring frequent temperature fluctuations. Future solutions for voltammetric/amperometric sensors as the LTCM devices can be depositing antipassivation materials (e.g., reduced graphene oxide-molybdenum disulfide nano-hybrid¹²³) onto the sensor surface to expand the lifetime, and modifying the sensor morphology with high conductive materials (e.g., metal organic frameworks (MOFs), nanorods, and graphene nanowalls) to expedite the electron transfer rate.

Potentiometric Sensors. Potentiometric sensors quantify target analytes by measuring the difference of open-circuit potential (OCP) between the ion-selective membrane (ISM)

Table 2. Typical Water Sensors for Data Acquisition in LTCM

Examples of LTCM in water systems						
Water sensor type	Advantages/ disadvantages for LTCM	Electrode (mechanisms)	Analyte/media	Detection range	Response time	Lifetime
Voltammetric/ampereometric sensors	Low detection limit	Surface grinded Cu electrode	COD in wastewater	10–1000 mg/L	Seconds	3 months
	High selectivity of micro impurity	Silicon-glass structured nitrite integrated sensor chip	NO ₂ ⁻ in drinking water	0.5–7 mM	20 s	19 days
	Simplicity of design					
	Passivation effect	Si wafer coated with Ti and Pt layer	Cl ⁻ , ClO ⁻ in drinking water	0.05–1 ppm	Seconds	6 days
Potentiometric sensors	Analyte consumption	Nickel-based (Ni(II)–curcumin) chemically modified electrode	Amoxicillin in wastewater	8.0–100.0 μM	Seconds	Not mentioned
	Reagent preparation					
	Fast response time	PVC-based ion sensitive field effect transistor (ISFET)	pH in wastewater	2–12	Seconds	3 weeks
	Wide detection range	Ammonium ionophore ISE with 2% MW-CNT	NH ₄ ⁺ in wastewater	0.015–1600 mg/L	Seconds	7 days
Conductometric sensors	No consumption of the analyte					
	Poor repeatability	Nitrate ionophore ISE with 5% PTFE	NO ₃ ⁻ in wastewater	0.5–64 mg/L	Seconds	20 days
	Temperature interference	Lead ionophore ISE with PEDOT conduct layer	Pb ²⁺ in wastewater	15–960 ppb	Seconds	2 weeks
	Only detect free ions	PDMS-modified graphite electrode	Phosphate in water sample	0.03–30 ppm	1 s	2 days
Optical sensors (fluorescence, nephelometry, ion chromatography, colorimetry, 3D image recognition)	Insensitive to light/DO					
	Simplicity of design	MOF-based glass slide	PFOS in groundwater	0.05–10 ⁵ ng/L	Seconds	6 days
	Low selectivity					
	Samples require pretreatment					
Biosensors (electrochemical and optical based)	No contact/consumption of the analyte	Silanized glass surface with covalently immobilized rhodamine–naphthalimide (fluorescence)	pH in wastewater	1.4–3.6	120 s	1 month
	Stable readings	Hydrogel-based glass substrate (fluorescence)	DO in water sample	0–21%	<90 s	2 weeks
	Various detection parameters	IR wavelength (940 nm) optical transducer (nephelometry)	Turbidity in river	0.1 > 4000 NTU	Seconds	22 days
	Bulky/complex setup, energy consumption	235 nm LED based absorbance detection (ion chromatography)	NO ₃ ⁻ /NO ₂ ⁻ in wastewater	NO ₃ ⁻ , 0.1–100 mg/L; NO ₂ ⁻ , 0.05–500 mg/L	<3 min	7 days
	User-unfriendly	Microcuvette based microfluidic chip (colorimetry)	Phosphate in river	0–20 mg/L	15 min	7 days
		Molybdenum blue assay microfluidics (absorptiometry)	Phosphate in coastal water	0.06–60 μM	5 min	60 days
		Gly-Gly-His-modified sensing areas (surface plasmon resonance)	Cu ²⁺ /Ni ²⁺ in drinking water	ppt–ppb level	30 s	1 week
	Slow response time	Glassware/flow cell (3D image recognition)	Bacteria counts in drinking water	/	10 min	11 weeks
	Low detection range	Molecular imprinting synthesized nanoparticles (surface plasmon resonance)	Diclofenac in wastewater	1.24–80 ng/mL	/	37 min lab test
	High sensitivity/selectivity	Biofilm with different endemic microorganisms on a nonoxidizable surface (potentiometry)	DO/ORP in wastewater	DO, 2–7 mg/L; ORP, 0–165 mV	Seconds	2 years

Table 2. continued

Examples of LTCM in water systems						
Water sensor type	Advantages/ disadvantages for LTCM	Electrode (mechanisms)	Analyte/media	Detection range	Response time	Lifetime
	Low power consumption or self-powered	Graphite anode matrixed with exocyttoplasmic cytochromes (potentiometry)	DO/conductivity in canal water	DO, 0–18 mg/L; conductivity, 0–1800 mS/cm	/	250 days
	Metabolic activity reduction	<i>Bacillus licheniformis</i> , <i>Dietzia maris</i> , and <i>Marinobacter marinus</i> from seawater (fluorescence)	BOD in seawater	0.2–40 mg/L	3.2 min	6 months
	Slow response time	AlaDH as bioreceptor (amperometry)	NH ₄ ⁺ in wastewater	0.1–300 mM	20 s	120 days
	Short lifespan	Carbon paper anode, Pt cathode (microbial fuel cell biosensor)	VFAs in wastewater	5–40 mg/L	1–2 min	5 days
	Large sensing surface area required	Enzyme (tyrosinase) and MW-CNT (amperometry)	Quinine	0–2000 nm	30 min	Not mentioned

coated working electrode and the reference electrode in the absence of current flow¹²⁴ (Figure 3c). Potentiometric sensors have been widely used for long-term (>1 week) and continuous (sensing interval <30 s) monitoring of ions such as protons (pH), nitrogen species (e.g., NH₄⁺, NO₃[−], and NO₂[−]), and heavy metals (e.g., Pb²⁺) based on the specific affinity of target ions to the ISM matrix¹²⁵ (Table 2). Even though potentiometric sensors are the top candidate for LTCM, the main limitation is that the sensing scope is only applicable to ions. Also, the morphology change of the sensor ISM matrix (e.g., aqueous layer formation inside the ISM matrix,¹²⁶ physical damage by the debris and particles attached,¹²⁷ biofouling,¹²⁸ and ISM component leaching¹²⁹) deteriorates ion affinity and ion diffusion in the ISM matrix and causes measurement errors, and finally declines the long-term accuracy of sensors. Furthermore, because contaminant concentrations are quantified using the Nernst equation ($E = E^0 + \frac{RT}{zF} \log a$), the signal readings of potentiometric sensors are temperature-dependent, and logarithmic response can result in drastic reading drift. Additionally, data acquisition using potentiostats suffers from acute variation of the initial OCP readings among different types of sensors and thus imposes the need for frequent recalibration over time¹³⁰ (Figure 3c). Future solutions can focus on sensor material innovation (e.g., antifouling coating with zwitterionic copolymers and silver nanoparticles) to prevent ISM from deterioration (Figure 3d) and development of novel data processing programs (e.g., Coulometric Signal Transduction,¹³¹ Bayesian Source Separation,¹³² and Observations Data Model¹³³) to enhance the sensor accuracy and sensitivity.

Conductometric Sensors. Conductometric sensors quantify the analyte concentration by measuring the resistance/conductivity variation on the conducting layer of the working electrode (Figure 3e).¹³⁴ As impedance measurement devices, conductometric sensors are suitable for monitoring certain types of water contaminants (e.g., PFCs¹³⁵ and *Escherichia coli*¹³⁶) that are unable to trigger electrochemical reactions or adsorption/transfer processes.^{137,138} For example, conductometric sensors monitored PFCs in groundwater for 6 days with a detection limit of 0.05 ng/L (Figure 3f, Table 2). In addition, electrical resistance sensors performed real-time continuous online monitoring of water pipeline corrosion for more than 10 days with a sensing interval of 1 h.¹³⁹ However, conductometric methods are fundamentally nonselective unless conducting layers (e.g., zeolites and hydrogel) are employed for a specific target analyte^{140,141} (Figure 3e). Additionally, several possible issues (e.g., temperature fluctuation, the conducting layer peeling off from the electrode surface, and sensor conductance variation¹⁴²) can cause long-term instability (i.e., measurement drift) of conductometric sensors. Future solutions for conductometric sensors include strengthening sensitivity/selectivity and accelerating the transfer rate of ions and electrons on the sensor surface by using nanoscale and layer structured materials such as 2D carbon nanotubes.

3.2. Optical Sensors for LTCM. Optical sensors measure the target analyte by establishing the relationship between water parameters and optical signals (e.g., absorbance and fluorescence)^{16,143,144} (Figure 3g). Three groups of optical sensors reviewed here are fluorescence-based optical sensors, absorbance-based optical sensors, and other types of optical sensors (e.g., colorimetric sensors, surface plasmon resonance (SPR) sensors).

Fluorescence-Based Optical Sensors. Fluorescence-based optical sensors are the largest group of optical sensors with the mechanism that fluorophores are excited by a given analyte and emit light radiation at specific wavelengths unique to this analyte. The measurement is performed based on the fluorescent response to the indicator immobilized in a polymeric support.¹⁴⁵ Current studies on fluorescence-based optical sensors include expanding the measurement capacity (e.g., Fe^{3+} ion detection based on a quantum dot-doped hydrogel¹⁴⁶), and applying online textural image analysis for monitoring water processes (e.g., coagulation and flocculation).¹⁴⁷ Attributed to the long response time (usually >1 min) caused by slow mass transport to reach the required equilibrium concentration on the sensor surface,¹⁴⁸ fluorescence-based optical sensors are not suitable for real-time monitoring and require frequent maintenance (Figure 3h,i, Table 2). Long-term performance of fluorescence-based optical sensors has been hindered by the decay of fluorescence indicators resulted from crystallization in the polymeric supports.¹⁴⁹ Another roadblock is the swelling of polymeric supports in water (e.g., poly(methacrylic acid) starts swelling at the pH of 4¹⁵⁰), which weakens the covalently immobilizing ability with indicators.¹⁵¹ The selectivity of fluorescence-based optical sensors can also be impaired by the similar fluorescence spectra from certain analytes (e.g., dinitrotoluene and trinitrotoluene¹⁵²) in the complex medium such as WW. MOFs (e.g., Zr(IV) MOF (UiO-67-bpy)) are a promising candidate to ameliorate the immobilizing ability, since the confined space provided by MOFs enhances the supra-molecular interactions inside the supporting matrix.¹⁵³

UV Absorbance-Based Optical Sensors. UV absorbance-based optical sensors are a subcategory of optical sensors capable of quantifying the analyte using the absorbance of radiation in the UV–vis range (usually from 100 to 400 nm).¹⁵⁴ UV absorbance-based optical sensors have been widely used for measuring nutrients (e.g., nitrate¹⁵⁵) and organic compounds (mainly chromophores that contain valence electrons of low excitation energy¹⁵⁶) in water (Table 2). The major challenges for the long-term deployment of UV absorbance-based optical sensors are the low selectivity caused by interference absorbance in the WW,¹⁵⁷ measurement drift, and poor detection limit from the noises such as temperature fluctuation and water flow during the onsite monitoring.¹⁵⁸ Additionally, standard UV light sources (e.g., a mercury lamp) suffer from a short lifespan and high power consumption.¹⁵⁹ To elevate the LTCM application of UV absorbance-based optical sensors, future studies can focus on combining data processing with the analysis of multiple wavelengths results to enhance the sensing selectivity (e.g., multiple linear regression models have been used to quantitatively analyze the total organic carbon (TOC) concentrations in DW and NRW¹⁵⁶) and applying light-emitting diodes (LEDs) light source equipped with capillary column detectors to prolong the sensor lifetime and reduce the noise level.¹⁵⁸

Other Optical Sensors. Other optical sensors including nephelometric, colorimetric, and surface plasmon resonance (SPR) sensors have been employed in water systems (Table 2). Nephelometry sensors measure water parameters (e.g., turbidity) by detecting the light energy scattered or reflected toward a detector, and can continuously monitor suspended particulate matters for more than 20 days in rivers^{160,161} (Table 2). However, nephelometric sensors are deficient at measuring the particles smaller than 200–300 nm in diameter

due to their low scattering cross sections,¹⁶² and thus failing to monitor soluble contaminants in WW.¹⁶³ Colorimetric sensors utilize the color change from the interaction (e.g., oxidation/reduction reactions) between the target analyte and the nanoparticles/nanozymes on the sensor nodes under light illumination.¹⁶⁴ By connecting the sensor nodes with a smartphone app capable of color differentiation, colorimetric sensors can quantify the phosphate concentration in a river for 7 days with the upper detection limit of 20 mg/L¹⁶⁵ (Table 2). However, colorimetric sensors are unable to discriminate a specific component in a mixture media (e.g., Hg^{2+} in WW¹⁶⁶) since the color change can be interfered by numerous factors (e.g., pH, suspended solid, and organic matters¹⁶⁷). SPR sensors and ion chromatography have been used for LTDM (monitoring interval: ~3 min) of nitrogen and heavy metals at the ppb and even ppt level for 1 week (Table 2), but the main issue for extending the monitoring duration is the high cost incurred by the instrumentation itself and the complicated site-specific calibration procedures.¹⁶⁸ Reducing the light source power consumption/cost and developing novel light response materials to shorten the response time are critically demanded for future LTCM application of optical sensors.

3.3. Biosensors for LTCM. Biosensors measure the target analyte qualitatively or quantitatively by converting the observed responses into the measurable electrical or optical signals, which is carried out by the biological recognition elements such as enzymes and microorganisms¹⁶⁹ (Figure 3j). Biosensors have gained enormous attention in the past decade, especially for monitoring nutrients and toxic analytes such as biological oxygen demand (BOD),¹⁷⁰ microbes,¹⁷¹ nitrogen,¹⁷² pathogens,¹⁷³ and heavy metals¹⁷⁴ with the response time of seconds (Figure 3k, Table 2). Microbial fuel cell-based and biofilm-based sensors were developed for monitoring contaminants in WW and demonstrated distinct features such as self-sustained operational mode, small reagent volume (<30 mL^{175,176}), low cost (intrinsic microorganisms as recognition elements),^{177–179} and clear correlations between potential (mV) output and contaminant concentration. Biosensors are also superior candidates for biological material detection in water systems. For example, biosensors utilizing mediated electron transfer (MET)-type bioelectrocatalysis can be used for microbe activity detection based on the electron transfer between microbes and electrode.¹⁷¹ However, these sensors may not be suitable for continuous monitoring as they are typically nonselective and many toxic contaminants (e.g., Hg^{2+} and Cr^{6+}) can inactivate the microorganisms in these sensors and generate uninterpretable signals.^{177,180,181} Additionally, enzyme-based and microorganism-based electrochemical/optical biosensors suffer from low signal outputs in the water with low conductivity (e.g., river and drinking water),¹⁸² and require a large sensor surface area and additional analyte solution to attain usable response magnitudes.¹⁸³ Moreover, the decline of metabolic activities and the inactivation of microbial cells result in rapid deterioration of signal intensity and short lifetime of bioreceptors for LTCM. To address this challenge, recombinant enzymes or genetically modified “super bacteria” that can survive in WW could be developed as the recognition elements in the construction of highly stable biosensors.^{184,185}

3.4. Sensor Development for LTCM of ECs: Current Challenges and Future Perspectives. Certain types of routine water parameters and contaminants might only need STDM, STCM, and/or LTDM. For example, turbidity in a

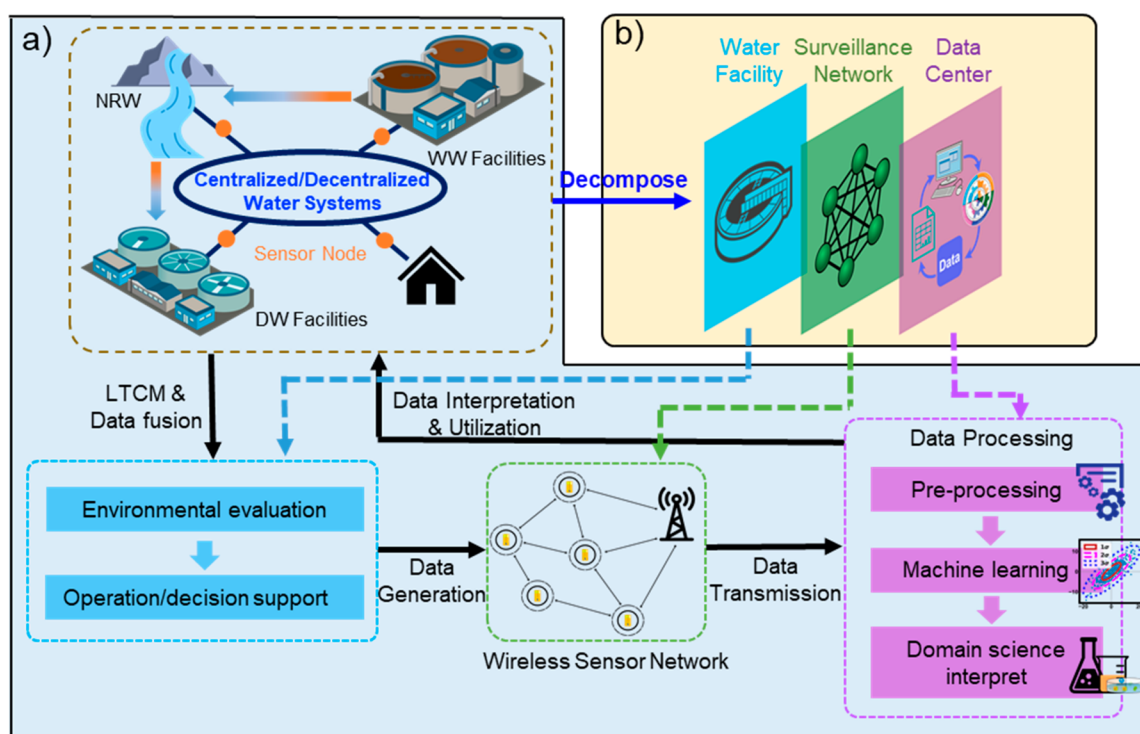


Figure 4. A data-driven decentralized water system paradigm. (a) A water facility network with a strong connection through data flow. (b) A decomposition of water systems into three levels (data, parameter, and system).

DW influent is normally monitored in a STDM mode, since it is relatively stable and does not represent a risk to public health under normal circumstances. Also, it can be correlated with bacterial counting (conducted in STDM) and total suspended solid (TSS) measurement to avoid misinterpretation.²⁰³ The temperature in NRW (e.g., groundwater and surface water) only needs LTDM due to its slow variation throughout a season.²⁰⁴ By contrast, ECs are ubiquitous in both natural water environments and engineering infrastructures, and have complicated transport pathways and long-lasting impacts,^{205,206} making the LTCM of ECs critical to execute efficient treatment/control methodologies and alleviate public concerns (Figure 2b). ECs in water systems are comprised of an extensive spectrum of compounds including organics with complex functional groups (e.g., pharmaceutical and personal care products), long chain carbon backbones (e.g., PFCs), polymers (e.g., MPs), and microbial related substances (e.g., antibiotic resistant gene (ARG), antibiotic resistant bacteria (ARB)) in a trace level (ppb or even ppt).²⁰⁷ Advanced treatment processes such as AOPs, NF, and RO have been studied at the lab scale to remove ECs. For example, AOPs with the ozone dose ranging from 0.82 to 2.55 mg O₃/mg DOC (dissolved organic carbon) removed 99% of ECs including antibiotics, steroid hormones, and antineoplastics.²⁰⁸ However, these processes pose high energy demands and generate toxic byproducts (e.g., trihalomethanes (THMs)²⁰⁹). Existing monitoring devices are unable to monitor the fate and transport (e.g., diffusion, sorption, and degradation) of ECs in a long-term and continuous mode (Table 2). Optical analysis methods using Fourier-transform-infrared (FTIR) imaging^{210,211} and enhanced Raman scattering^{212,213} have been applied to quantify ECs such as microbeads, since they can identify all the molecular and functional groups present in plastic polymers. However, complicated pretreatment, tedious

measurement protocols, and bulky equipment settings hinder their LTCM ability. As for electrochemical sensors, the sensor readings for ECs at ppb or ppt level (e.g., <0.44 ng/L PFOS in drinking water,²¹⁴ <10⁻⁴–10⁻³ ARGs/16S rRNA gene in drinking water²¹⁵) are easily interfered by contaminants (e.g., ammonium and chloride) present at much higher concentrations (e.g., 1–40 mg/L) in water.

Future studies for LTCM of ECs can focus on the combination of multiple spectroscopic methods (e.g., transmittance/laser-based devices) to construct a comprehensive measurement matrix with a low detection limit and high stability. Moreover, facile portable data logging devices easy to be carried and handled for quantitative on-site optical analysis should be developed as the alternative platforms for ECs monitoring.²¹⁶ For example, a portable colorimetry sensor using a smartphone to quantify fluoride in the drinking water has shown a potential for LTCM of ECs in a user-friendly mode.²¹⁷ For electrochemical sensors, morphology modifications (e.g., nanocomposites with high electrocatalytic activity,²¹⁸ MOFs with specific microporous frameworks²¹⁹) could be a future solution to improve the sensing detection limit and selectivity during the ECs LTCM.

4. CURRENT STATE AND CHALLENGE OF DATA PROCESSING FOR LTCM

After data acquisition, the next step for LTCM is to deploy data processing methodologies to ensure the accuracy and stability of the sensor data collected. Establishing a platform capable of processing real-time, high-fidelity, and full-scale data is vital to achieve a data-enabled system. In this section, we demonstrate the current state of data collection and data processing for LTCM. Currently, short-term and discrete monitoring coupled with *ex situ* lab-based measurement are still the mainstream in water quality measurement. Although

the data sets of those parameters can be combined with other long-term continuous counterparts to form a higher dimension data matrix, the vacant values create large sparsity and compromise the reliability of data processing and water system snapshot. Limited by discrete data collection, feedback adjustments of water parameters are neither timely nor precise from STDM and LTDM data, which makes operations or emergency responses deviate from the actual circumstance in water systems in terms of time and extent. This puts forward a high requirement of data collection and processing algorithms for precise depiction of water systems.

4.1. Data Collection for LTCM through the Sensor Networks. High quality data processing, system modeling, and feedback control require collection of vast amounts of data with wide spatial and temporal variability. In a recent study, 22 water quality parameters (e.g., pH, electrical conductivity, and chloride) from 197 sample locations in a DW system were systematically evaluated.²²⁰ Similarly, another study assessed groundwater quality by incorporating 23 parameters from over 40 regional DW/WW companies with fecal coliform as the pathogen indicator.²²¹ With data accumulating over time, its collection and storage could lead to an unexpected burden for data transmission and processing.²²² However, a study exploring benchmark sensors for on-site monitoring in a WW treatment plant reveals that proper operation setups (e.g., solid retention time and aeration rate) can maintain and even improve the sensor accuracy, and integration of a sensor surveillance network and control can enhance the robustness of remote monitoring systems.²²³ In conventional centralized water systems, water network distribution depends on a centralized cloud model that has a potential risk of exposure to cyberattack with the growing number of network nodes.²²⁴ From the standpoint of security and privacy, each end-user may act as a bottleneck or a failure point to disrupt the entire water network.²²⁵ LTCM can break centralized water systems into smaller units based on regions and functions, within which water parameters become more specific and data throughputs will be more tolerable.^{223,226} Furthermore, the dynamics of multiple water systems (e.g., decentralized water treatment units and water networks) can be associated digitally through data flow (Figure 4a). As elementary water distribution units become smaller, LTCM sensor networks can be operated compatibly with the water system configuration, which enables real-time monitoring and adjustment of water quality parameters and water facility operations, expands the security capability of decentralized water systems, and protects the water sensor networks from cyberattack.^{227–230}

4.2. Data Processing to Enhance the Accuracy and Interpretability of LTCM. Appropriate data processing and analysis algorithmic tools such as statistical analysis,²³¹ regressions,²³² Fourier transform,^{233–235} and machine learning^{236–238} are required to calibrate sensor readings and attain trustworthy data. On-site testing data are usually discrete within a short period of time (e.g., STDM and STCM), resulting in a limiting temporal resolution. In contrast, LTCM can resolve this hurdle with transitory and flexible data sampling interval at the minute or even second level of precision. However, fully utilizing LTCM to achieve a prediction forward mode in water systems requires the data processing algorithms being redesigned to handle high data throughput, including identifying abnormalities from raw sensor data and evaluating water quality parameters over a long-term period.

Supervised learning algorithms (e.g., support vector machine, neural networks, and random forest) have high efficiency in the preventive maintenance toward data distortion and water system snapshot.^{239,240} A study showed that with discrete training data alone, the noise from interference ions (e.g., K^+ , Na^+ , Ca^{2+} , and Mg^{2+} , all governed by the Nicolskii–Eisenman equation) has been rectified through a back-propagation neural network armed with genetic independent component analysis.²⁴¹ As for the evaluation of the environmental impact in complex scenarios, continuous data obtained in LTCM are required to fine-tune water parameters and acquire periodic variation information in water systems. In a recent work of wastewater quality prediction with wavelet denoising techniques, Radial Basis Function Neural Network and Adaptive Neuro-Fuzzy Inference System were used to augment existing algorithms and determine significance of input variables for 12 water parameters including conductivity, turbidity, NO_3^- , and *E. coli*.²⁴²

The ML structure is divergent from assembled knowledge blocks in human natural logic,^{243–246} thereby more information beyond the human analytical capability can be captured in the high dimensional sparse data matrices with both discrete data and continuous data. As time evolves, the integration effect of variation in each layer can be well handled by ML. Even for trace contaminants (e.g., ECs) with more abnormalities (as they are exceptionally close to detection limits), their distribution can be predicted by evaluating periodic correlation with other water indexes in a long period of time to ensure reliability. A recent major endeavor is the development of multilayer perceptron neural networks to predict the translocation of ECs including benzo[*a*]anthracene, chrysene, perfluorobutanesulfonate (PFBS), and PFOA, in which fuzzy logic was used to determine the physiochemical cutoffs and eliminate the partition effect.²⁴⁷ With key water parameters being digitalized and visualized through data acquired from LTCM, a modern water system can be decomposed into different dimensional layers connected through data flow (Figure 4b).

4.3. Current Challenges and Future Perspectives of Reliable Data Processing. Challenges for water system data analysis may arise from the data availability, and the design, operation, and maintenance of algorithms on the top of data. To improve data accessibility, digital and smart sensing systems can be established for acquiring LTCM data for different types of water (e.g., DW, WW, and NRW) on a large scale and construct a comprehensive measurement matrix with a low detection limit and high stability. As for accurate data processing and analysis, integrating different monitoring strategies (LTCM, LTDM, STCM, and STDM) can generate data-driven models to predict pollution events and guide contaminant removal processes. Moreover, multisensor fusion techniques based on extended machine learning algorithms (e.g., neural network) can be applied to integrate multiple water parameters (e.g., flow rate, pH, and inlet/outlet contaminant concentrations) at different spatiotemporal resolutions and perform automated fault detection and diagnosis for contamination prevention and decision-making in water facilities.²⁴⁸

5. CURRENT STATE AND CHALLENGE OF DATA APPLICATION FOR LTCM

After LTCM data are acquired and processed, they will be applied to implement efficient operational strategies in water

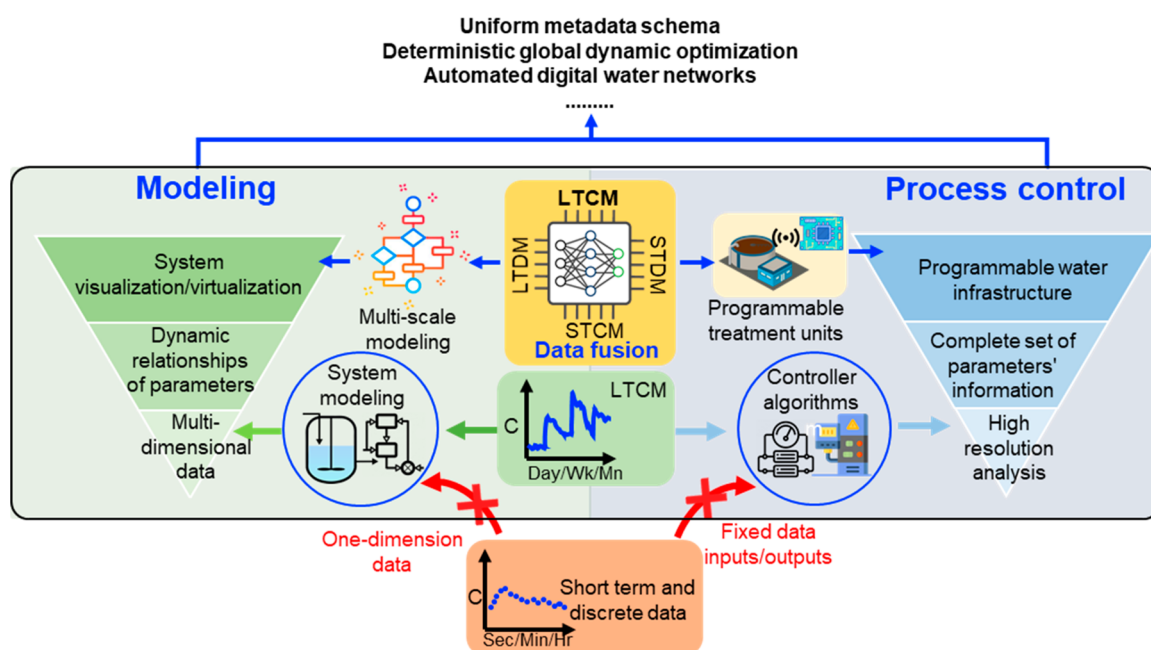


Figure 5. Comprehensive diagram showing the critical role of LTCM and data fusion in water system modeling and process control from the 3-layer hierarchy perspective (sensor data, water parameters, and system level).

systems. In this section, we use water system modeling and process control as two distinct examples to illustrate LTCM data application and expound their status and challenge. Most of the models applied in water systems (e.g., anaerobic digestors, sequencing batch reactors (SBR), and DWDSs) and treatment processes (e.g., disinfection and BNR) still rely on the water quality data obtained from short-term and discrete monitoring and/or historical records. For example, Anaerobic Digestion Model No. 1 (ADM1) mainly depends on discrete monitoring data (e.g., flow rate, pH, and biogas) with one data point collected per day or even per week.²⁴⁹ Proportional-integral-derivative (PID) control has also been widely used for various process control systems.²⁵⁰ However, most of the PID control methodologies are developed based on STDM or STCM data with the fixed parameter inputs that are unable to predict the time-varying fluctuation and heterogeneity in water systems. For this reason, innovation in system modeling and controller algorithms combined with metadata schemes collected from multiple dimensions is essential to execute efficient operational strategies and ensure system stability and robustness (Figure 5).

5.1. LTCM Application of High-Fidelity Profiling and Modeling. Achieving energy-efficient DW and WW treatment processes relies on the development of kinetic models (e.g., concentration addition (CA) model for disinfection by-products²⁵¹ and activated sludge model (ASM)²⁵²) and system/process visualization and virtualization (e.g., Visual 3D dissolution model²⁵³). However, these models have been established using data obtained from STCM and LTDM, such as bacteria count with duplicate samples for CA models²⁵¹ and Cu^{2+} concentration with a sampling interval of several hours in ASM.²⁵⁴ Recently, a net-zero-energy (NZE) model based on biomass energy recycling (a sampling interval of 1 day) has been deployed to simulate energy-efficient WW treatment processes, resulting in 79.5% offset of electricity and sludge disposal cost compared to conventional treatment processes.²⁵⁵ A computational fluid dynamics (CFD) model

with fixed water quality parameter inputs (e.g., total organic carbon (TOC), temperature, Br^- , and pH) obtained from STDM has been applied to predict the disinfection efficiency by simulating chlorine decay, pathogen inactivation, and byproducts formation in contact tanks.²⁵⁶ However, existing STDM and STCM approaches fail to adapt to vigorous water quality fluctuations throughout heterogeneous DW/WW treatment units and can only provide fixed inputs and outputs for model implementation. Although LTDM is capable of collecting real-time high-fidelity data, it cannot perform automatically and requires frequent manual maintenance and recalibration, posing an imminent challenge for system visualization and virtualization²⁵⁷ (Figure 5).

LTCM in conjunction with multivariate data analysis can procure both quantitative and qualitative information essential to combat the data sparsity and model insensitivity. LTCM is capable of providing data at multiple time scales to decode the relationships between water parameters (e.g., pH and oxidation reduction potential (ORP) for biogas production in AD reactors²⁵⁸) and promoting energy-efficient operation through system visualization. For example, a long-term relationship between anaerobic reaction time, denitrifying phosphorus removal rate and microbial community dynamics in the enhanced biological phosphorus removal systems were established through 2-month LTCM of NO_2^- and NO_3^- .²⁵⁹ Moreover, the open-access data stream consisting of high-dimensional data from different monitoring strategies including STDM, STCM, LTDM, and LTCM will enable a platform for evaluating the state-of-the-art multiscale water models (e.g., deep learning sensor fusion, artificial neural network (ANN)) to improve system resilience (Figure 5). For example, a multisensor fusion method based on Dempster-evidence theory was deployed to process simulated data as well as real-time long-term and short-term monitored data, demonstrating the capability to capture the occurrence of water contamination in DWDSs with an accuracy 1.2 times high than those only using long-term monitoring regime.²⁶⁰ In another

study, different types of operational data (e.g., discrete data for biogas, continuous data for pH and nitrogen species) collected over four years were interpreted using XGBoost and random forest algorithms, which were subsequently applied to visualize anaerobic codigestors and predict daily methane production with a reasonable R^2 value of 0.80–0.88.²⁶¹

5.2. LTCM Application of Process Control. Water systems require precise control strategies coupled with advanced sensing techniques to detect/correct operational failures and execute swift responses under varying conditions. Existing PID control is only tuned at the beginning of installation, resulting in low adaptability to dynamic variations.²⁶² By contrast, the model predictive control (MPC) methodology delivers highly accurate control with moderate complexity while allowing for performance improvement via sensor data as the external inputs.^{263,264} Until now, most of the MPC methods depend on classical physical-based unit operation models (e.g., ASM1 and sedimentation tank model^{265,266}) that normally function under discrete monitoring data (e.g., one data per day or even one data per week) to regulate the process variables. Such control strategies are limited to one-dimensional prediction (i.e., predict one water parameter from sensor outputs) with a low linear regression capability due to data sparsity and low temporal resolution. For example, the fusion-based genetic programming model built on four-year discrete data (one data/day) has been applied to estimate TOC concentrations in the Harsha Lake (Ohio, USA) to optimize treatment operation, but the calibration and validation plots exhibited low R^2 values (0.56 and 0.87, respectively²⁶⁷).

LTCM can provide high temporal scale and resolution analysis to assist fault detection and operation adjustment under transient shocks and promote the innovation of control strategies through continuous and synergistic cross-validation of model sensitivity and sensor data streams. Moreover, personalized data provided by integrating LTCM with other monitoring strategies (e.g., STDM, STCM, and LTDM) could facilitate data-driven models that access a complete set of information being collected across water systems, and finally achieve data dimension reduction through uniform metadata schema (e.g., Internet of Things (IoT) stack) toward programmable water infrastructure (Figure 5). For example, by incorporating STCM data (e.g., pH and ORP) and LTCM data (e.g., NH_4^+ concentration), a real-time control strategy was developed and validated throughout a 220-day period to control the duration of nitrification–denitrification phases in an SBR, accomplishing 98% oxidation of ammonium and 20% reduction of reaction time.²⁶⁸ This unique control strategy consists of high temporal resolution sensing data, data fusion/data-driven models, and deterministic global dynamic optimization, and offers superior performance over traditional control approaches.

5.3. Current Challenges and Future Perspectives of LTCM Applications. ML algorithms coupled with LTCM has demonstrated the capability of advancing predictability of water system modeling and control through learning patterns. However, those algorithms require large volumes of representative training data relied upon capable sensors that are severely under developed.¹² A critical step is developing reliable sensors and data processing algorithms to present real-time LTCM sensor data for variable inputs and complex dynamics.

Future applications of LTCM in water systems profiling/modeling could be utilizing the high temporal resolution data obtained by sensors to develop a digital twin toward smart water system management. With the provision of the high-fidelity LTCM profiles along with models development, a digital twin can form a central repository to advance predictive analytics, system optimization, and personnel training.²⁶⁹ Additionally, data-driven analysis based on LTCM data can offer diverse temporal resolutions for fault detection, variable prediction, and automated control in water processes.²⁴⁸

6. CONCLUSIONS, FUTURE OPPORTUNITIES, AND OUTLOOK OF LTCM

In this review, we elaborate a forward-looking roadmap of LTCM through a three-hierarchy perspective: sensor data, water parameters, and system level. We evaluate and analyze the entire route of LTCM consisting of data acquisition (sensor development), data processing (sensor network and algorithms), and data application (modeling and process control). We identify the roadblocks of applying LTCM in natural and engineering water systems and pinpoint the target areas supporting innovations in LTCM technologies. In this section, we lay out future opportunities of LTCM applications in four key domains, water, energy, sensing, and data, covering emerging topics ranging from fundamental scientific exploration to knowledge generalization in broad communities.

6.1. Water Safety and Public Health. LTCM generates comprehensive data sets capable of capturing the heterogeneous status of water system dynamics under both normal operation and transient shocks. A reagent-free electrochemical sensing device recently developed is capable of detecting the presence of SARS-CoV-2 in water within 5 min and lasting for 9 months,²⁷⁰ indicating that LTCM can closely track the chemical fingerprint of target analytes to alleviate the public concern. Moreover, LTCM provides adequate data across a broad time scale essential for building the finest water dynamics profiles that can be used to develop digital networks connecting water grids with smart-city infrastructure and promote fully integrated water utilities. For example, mass deployment of various water sensors (e.g., humidity, temperature, and pressure) in DWTPs and DWDSs has been executed to detect the water leakage in an IoT-based smart water microgrid.²⁷¹ For the future studies, we recommend building IoT-based smart water quality monitoring systems comprising multiple types of sensor nodes to generate LTCM data and extend the sensing coverage range. These large digital water networks possess a high execution speed and the capability to protect the water ecosystems. One notable success is the long-term chlorine surveillance from 2015 to 2019, during which data were collected using digital colorimeters and color wheels monitored by citizen scientists in Flint (Michigan, USA), offering a unique methodology to assuage public health concern after the Flint Water Crisis (2014–2015).²⁷²

6.2. Energy-Positive Treatment Process and Resource Recovery. Implementation of cost-effective and energy-efficient treatment processes requires accurate quantification of water constituents as well as formulating multiobjective programmable models for adaptive outputs and process control. By providing real-time *in situ* information of water systems, LTCM can facilitate stakeholders and decision makers to foresee imminent water-quality problems and execute swift responses. For example, metal concentrations (e.g., Li^+) can be continuously monitored in a capacitive deionization (CDI)

reactor, based on which energy consumption and metal recovery can be balanced.²⁷³ Moreover, multiple time-scale data sets in AD systems can be generated by integrating LTCM data with short-term and discrete data using sensor fusion, which can build the long/short-term memory networks to illuminate complex interactions among various parameters, advance system resilience, and maintain stable biogas production under system fluctuations and shocks.^{258,274,275} One future application of LTCM is to provide individualized data with high computational efficiency to accomplish energy neutrality of water–energy microgrids and determine the overall impacts of carbon footprint on climate change (e.g., CH₄ and CO₂ emission from AD systems) by providing closely monitoring the critical parameters with unprecedented spatiotemporal resolution, which cannot be achieved based on current practices.

6.3. Sensing Capability Innovations. LTCM data enable us to quantify the impacts of sensor modifications on the overall sensor performance, which can structurally guide future sensor development and material optimization. Developing innovative sensor materials is a vital strategy toward LTCM, such as anticorrosion materials (i.e., superhydrophobic electrically conductive paper²⁷⁶), antimicrobial/antiadhesive materials (i.e., silver nanoparticles²⁷⁷ and zwitterionic copolymers^{278,279}), outer layer protection (e.g., silicon rubber²⁸⁰), and high viscosity materials (e.g., poly(methyl methacrylate)²⁸¹). In addition, sensor data processing algorithms can be coupled with sensor material development to further elevate sensor performance. For example, a denoising data processing algorithm has been employed to quantify the impacts of polytetrafluoroethylene on potentiometric ammonium sensors in terms of accuracy and lifespan during a 20 day test in WW.²⁸² Furthermore, the data generated from LTCM delivers months/years monitoring scopes and minute- or even second-temporal resolutions, which can maximize the computing ability, predict sensor reading variation, and eliminate sensor data drift.²⁸³ Finally, we also suggest applying sensor arrays consisting of different types of miniature sensors for multiplexed detection of a broad spectrum of water parameters and using data fusion/ML algorithms to achieve high-resolution profiling in water systems.

6.4. Data Sharing and Workforce Development. Another step forward should be establishing an open-access metadata platform and advancing data accessibility for general end-users. The unified open-source metadata scheme constructed by the LTCM data library can develop new generation coproduction applications (e.g., real-time DW quality mobile apps²⁸⁴) that address the critical data management need for broad communities. In the meantime, feedback of LTCM implementations can be promptly collected by sharing a vast amount of water quality data sets, which will in turn accelerate the development of LTCM technologies. For example, an Observations Data Model database built by sharing the data stored from a Hydrologic Information System was executed to identify the anomalous performance (e.g., sensor reading drift, calibration error, and sensor fouling) of the pH sensors deployed in the Little Bear River (Utah, USA) for a month with a sensing interval of 30 min, through which sensor readings were corrected and adjusted to achieve high accuracy and reproductivity.¹³³ To take advantage of the data library, we advocate providing automated digital water networks (e.g., IoT, digital twin, and SCADA) in small-size water facilities and/or decentralized systems for evolving process monitoring

and control strategies and acquiring and sharing multiscale LTCM data among underdeveloped communities and groups to promote water data equity and diversity.

With the development of materials science, novel sensing technologies, and machine learning algorithms in recent years, we envision that more reliable LTCM results will be available through data acquisition, processing and application to achieve high-efficiency data-enabled utility operation through a three-layer hierarchy (sensor data, water parameter, and system level), thus allowing the stakeholders and decision makers to probe emerging problems swiftly and executing competent control methodologies in a timely manner.

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Notes

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