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EMERGING TOOLS FOR CONTINUOUS NUTRIENT MONITORING NETWORKS: SENSORS ADVANCING SCIENCE AND WATER RESOURCES PROTECTION[1]

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ABSTRACT: Sensors and enabling technologies are becoming increasingly important tools for water quality monitoring and associated water resource management decisions. In particular, nutrient sensors are of interest because of the well-known adverse effects of nutrient enrichment on coastal hypoxia, harmful algal blooms, and impacts to human health. Accurate and timely information on nutrient concentrations and loads is integral to strategies designed to minimize risk to humans and manage the underlying drivers of water quality impairment. Using nitrate sensors as the primary example, we highlight the types of applications in freshwater and coastal environments that are likely to benefit from continuous, real-time nutrient data. The concurrent emergence of new tools to integrate, manage, and share large datasets is critical to the successful use of nutrient sensors and has made it possible for the field of continuous monitoring to rapidly move forward. We highlight several near-term opportunities for federal agencies, as well as the broader scientific and management community, that will help accelerate sensor development, build and leverage sites within a national network, and develop open data standards and data management protocols that are key to realizing the benefits of a large-scale, integrated monitoring network. Investing in these opportunities will provide new information to guide management and policies designed to protect and restore our nation's water resources.

(KEY TERMS: sensors; nutrients; water quality; information management.)

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INTRODUCTION

Protecting the quality of water in the nation's streams, rivers, lakes, and estuaries is of critical importance to sustaining both human and ecosystem health. Nutrient enrichment is a particular concern as it can lead to harmful algal blooms (HABs) and hypoxia in freshwater and coastal environments (e.g., Smith *et al.*, 2006), as well as human health effects (Bryan and Loscalzo, 2011; Brender *et al.*, 2013). Accurate and timely information on nutrient concentrations and loads is integral to efforts designed to minimize water quality impairment by managing nutrient sources and transport. This is particularly true, given the costs of developing and implementing nutrient reduction plans to restore or maintain water quality. For example, the cost of implementing best management practices (BMPs) developed by states in the Chesapeake Bay watershed to comply with total maximum daily loads is estimated at about US$900 million per year for full implementation (Kaufman *et al.*, 2014).

Much of our current understanding of the patterns and trends in nutrient concentrations and loads (as well as other water-quality constituents) is based on traditional monitoring approaches, e.g., discrete samples collected manually at weekly to monthly intervals followed by days to weeks for laboratory analyses to be completed. While this low temporal frequency approach — coupled with modeling and statistical techniques — has yielded critical information, more timely and accurate indications of water quality impairment could help resource managers and policy makers identify specific causes, assess the effects of remedial actions, and develop more effective responses. This is particularly important for episodic events such as floods that are difficult to anticipate but can have significant and long-term ecological, economic, and human health effects.

Sensors and associated physical and cyberinfrastructure — the telecommunications, collection platforms, data standards, and data management tools required to transform data into information in a timely manner — are becoming increasingly important for water quality monitoring and associated water resource management decisions (Horsburgh *et al.*, 2011; Murdoch *et al.*, 2014). Water quality sensors allow for nearly continuous (e.g., seconds to minutes) measurements, thereby reducing the likelihood that changes in water quality are missed or obscured as often happens with infrequent discrete sampling alone (Cassidy and Jordan, 2011). Furthermore, the transmission and analysis of continuous data in real time ensures that water management decisions can be made immediately. The combined temporal and spatial richness of water quality data from sensors also allows for dynamic queries and interactive time displays to identify the initiation and termination of water quality events that may be transient in time and/or spatially distinct.

Despite these benefits, the broad adoption and use of water quality sensors remains limited by a variety of factors including instrument acquisition and maintenance cost, ease-of-use, and data management challenges. Focusing on nitrate sensors as the most mature of the *in situ* nutrient sensor technologies, we describe the types of applications in freshwater and coastal environments that are likely to benefit from continuous, real-time water quality data, as well as a framework to accelerate and support their broader use. While the authority to manage water resources in the United States (U.S.) is largely delegated to states, tribes, and local municipalities, the consortium of federal agencies represented by the authors, and others, have an important role to play in the science and management of water quality ranging from drinking water protection to coastal fisheries and associated economic sustainability. Integration of leveraged investments by these and other national and international agencies and organizations through improved data standards, common methodologies, and guidance and support for deployment and data management activities can both accelerate the adoption of promising technologies and ultimately improve the science and management of our water resources.

CONTINUOUS NUTRIENT MONITORING: WHY NOW?

Nutrients — primarily nitrogen and phosphorus — are fundamental components of living organisms and critical to the global production of food and fiber. However, excessive nutrient levels that are largely the result of the production and use of inorganic fertilizers, animal manure, and discharge of human wastewater have dramatically altered and continue to shape aquatic environments (Richardson and Jørgensen, 2013). The effects of excess nutrients in waterways range from human health impacts caused by drinking water contamination, to HABs and hypoxia in freshwater and coastal ecosystems (Heisler *et al.*, 2008; Erisman *et al.*, 2013), all with substantial economic and ecological implications. For example, a recent study (Sobota *et al.*, 2015) estimated the potential health and environmental impacts of reactive nitrogen release to aquatic systems totaled US$210 billion per year in the U.S. in the early 2000s, with estimates ranging from $19 billion annually due to drinking water impacts to $78 billion related to impacts on freshwater ecosystems.

Despite major federal, state, and local efforts to control their sources and transport, nutrient concentrations in many rivers and aquifers across the nation have largely remained the same or increased since the early 1990s (Dubrovsky *et al.*, 2010). For example, an estimated 14,000 water bodies nationwide are affected by excess nutrients (State-EPA Nutrient Innovations Task Group, 2009). Coastal eutrophication also remains problematic and widespread, with 65% of the nation's major estuaries showing moderate to high levels of nutrient pollution (Bricker *et al.*, 2007; Figure 1).

Addressing the impacts and costs of nutrient contamination on water quality can now be greatly assisted by the new capabilities for continuous monitoring. The recent emergence of two related areas of technology in particular — reliable sensors for measuring nutrient concentrations *in situ* and tools for integrating and managing large datasets — have positioned the field of continuous water quality monitoring to rapidly move forward. Both sensor and data management technology have advanced to the point where sensors will quickly become common and critical tools not only in water quality research and monitoring, but also in water resource management.

The Emergence of Nutrient Sensors

Nutrient monitoring in surface water dates back to at least the late 1800s when the reliability of drinking

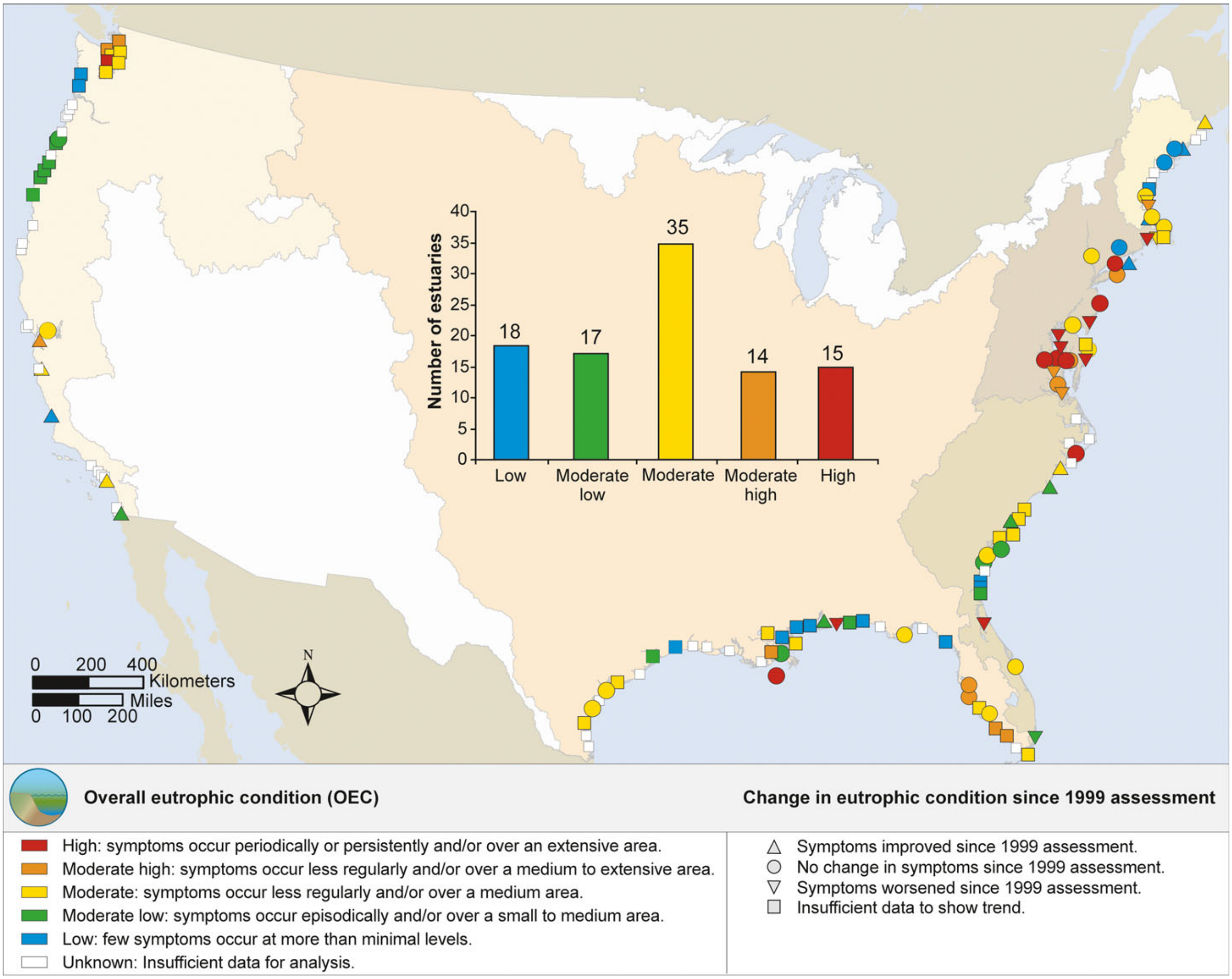

FIGURE 1. Overall Eutrophic Condition of U.S. Estuaries (from Bricker *et al.*, 2007). Colors represent the overall eutrophic condition while shapes represent the change in eutrophic condition since 1999 (see legend).

water sources for population centers became a concern (Myers, 2015). Then, as now, the primary monitoring approach has been infrequent discrete sample collection followed by wet chemical analysis in a laboratory. The ability to measure nutrient concentrations *in situ* using field sensors developed relatively recently with the application of ion-selective electrodes (ISE) in the 1970s (Langmuir and Jacobson, 1970) and the emergence in the last 20 years of wet chemical analyzers and nonchemical optical sensors that could be deployed in the environment (Jannasch *et al.*, 1994; Finch *et al.*, 1998; Johnson and Coletti, 2002). Much of the focus of sensors development has been on nitrate, given that it is both problematic for water quality and amenable to *in situ* measurements by different technologies. However, ISE and wet-chemical sensors for ammonium and orthophosphate also have a history of use for *in situ* monitoring and research. Wet chemical orthophosphate sensors, in particular, show promise for quantifying high frequency changes in water quality in response to hydrologic and biological forcings (Cohen *et al.*, 2013; Gilbert *et al.*, 2013; Outram *et al.*, 2014; Bowes *et al.*, 2015; Sherson *et al.*, 2015).

Different nutrient sensor technologies have advantages and disadvantages in terms of accuracy, cost, reliability, and ease-of-use (Table 1). For example, ISEs for nitrate are relatively inexpensive and easy to use, but have much lower accuracy and higher drift than wet chemical or UV nitrate sensors. However, the primary benefit from all three is the high temporal frequency of the data collection (e.g., seconds to minutes) which captures changes in water quality that occur at short time scales (Cassidy and Jordan, 2011; Jones *et al.*, 2012). For example, data from the Potomac River illustrate the daily, event, seasonal, and annual variability in nitrate concentrations that can be measured with continuous monitoring but would likely be missed with traditional monthly discrete sampling (Figure 2). The other primary benefit is in the real-time delivery of data rather than delays of days to weeks common for laboratory analyses and communication of results. This allows for water management decisions to be made in real time as is demonstrated by the use of nitrate sensor data by the Des Moines Water Works to determine and anticipate the need for operating costly nitrate removal systems for drinking water (Figure 3).

The current generation of nutrient sensors being used for water quality monitoring was originally developed for use in specific applications that influenced instrument design and specifications (Pellerin *et al.*, 2013). For example, UV nitrate sensors were primarily developed for use in either wastewater treatment facilities or in the coastal ocean, both of which have specific and unique needs in terms of the sensitivity, linear measurement range and anti-fouling components. Similarly, early versions of wet chemical orthophosphate sensors were primarily developed for applications in coastal settings with reduced fouling and lower suspended sediment concentrations than measured in many rivers and streams. While many of these instruments have since been adapted for use in rivers, lakes, and estuaries, the next generation of nutrient sensors will likely be optimized for freshwater systems by recent efforts to accelerate the development, production and use of affordable, reliable and accurate sensors in a range of environments (e.g., Nutrient Sensor Challenge; www.nutrients-challenge.org/).

Tools for Integrating and Managing the "Data Deluge"

While the continuous monitoring of nutrients is a significant advance in attempts to understand and

TABLE 1. Advantages and Disadvantages of Commercially Available Nutrient Sensor Technologies.

Type	Principle	Advantages	Disadvantages
Optical (UV) sensors	Spectral absorption by a photometer	High resolution, accuracy, and precision Chemical-free Fast response time Additional optical information in spectra	Expensive (>$15,000) High power requirement and maintenance costs Only available for nitrate
Wet-chemical sensors	Wet chemical colorimetric reaction with detection by photometry	High resolution, accuracy, and precision Potential for *in situ* calibrations Relatively fast response time Available for ammonium, nitrate, and phosphate	Expensive (>$10,000) High power requirement and maintenance costs High potential for fouling Requires reagents (generates waste)
Ion-selective electrodes (ISE)	Direct potentiometry between a sensing electrode and a reference electrode	Inexpensive (<$1,000) and easy to use Fast response time Not influenced by color or turbidity Available for ammonium and nitrate	Low resolution, accuracy, and precision Subject to ionic interferences High instrument drift Limited shelf life

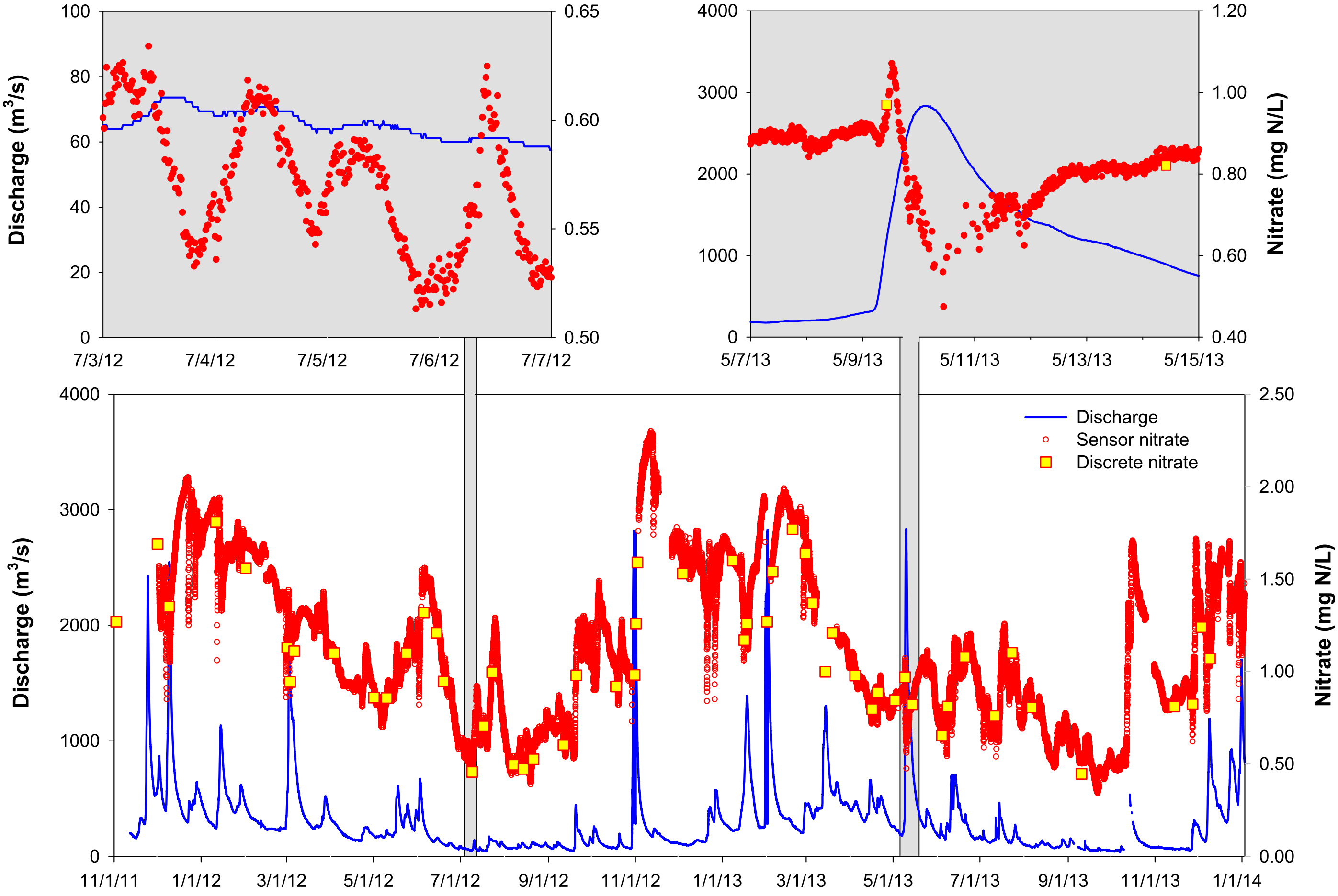

FIGURE 2. Time Series of Nitrate for the Potomac River at Little Falls (USGS Station 01646500) Showing the Time Scales of Variability in Nitrate Concentrations. Continuous (15 min) nitrate sensor data are shown in red circles, while biweekly and event-based discrete sampling is shown in yellow squares. Note different scales on axes.

monitor water quality, improvements in our ability to integrate, process and analyze large datasets are also needed (Porter *et al.*, 2012). For example, continuous monitoring of a single parameter at 15 min intervals results in over 35,000 measurements per year, with that number easily increasing by orders of magnitude when additional sensors and diagnostic data are also included. This is in contrast to traditional field sampling programs that typically collect 12-18 samples per year, albeit with rich metadata associated with each of those discrete data points. Given this “data deluge” (Baraniuk, 2011; Porter *et al.*, 2012), new and emerging data standards, improved telemetry, and new data management approaches are critical, particularly for the establishment of sensor networks in which data are collected and shared amongst multiple parties.

The Consortium of Universities for the Advancement of Hydrologic Sciences, Incorporated (CUAHSI) has demonstrated the potential for sharing sensor data through the CUAHSI Hydrologic Information System (HIS; https://www.cuahsi.org/AboutHIS). The CUAHSI approach illustrates how defining standard protocols for publishing data facilitates the discovery of data from various sources or locations and allows for the incorporation of those data into other third-party applications. Since the initial implementation of the HIS, the Open Geospatial Consortium (OGC) has finalized web service interface standards for sensors as well as standard information models for sharing sensor data (http://www.opengeospatial.org/standards/sos). These standards have created the possibility for an interoperable sensor network where systems and devices can exchange and interpret data for not only nutrient sensors, but virtually any sensor providing information on both water quantity and quality.

The Open Water Data Initiative (OWDI) provides a federal vision for how water data can be made both discoverable and interoperable, and the framework envisioned under OWDI supports the development of an interoperable sensor network. In order for such a sensor network to be successful, however, the principles of the OWDI need to be followed, including: (1) a

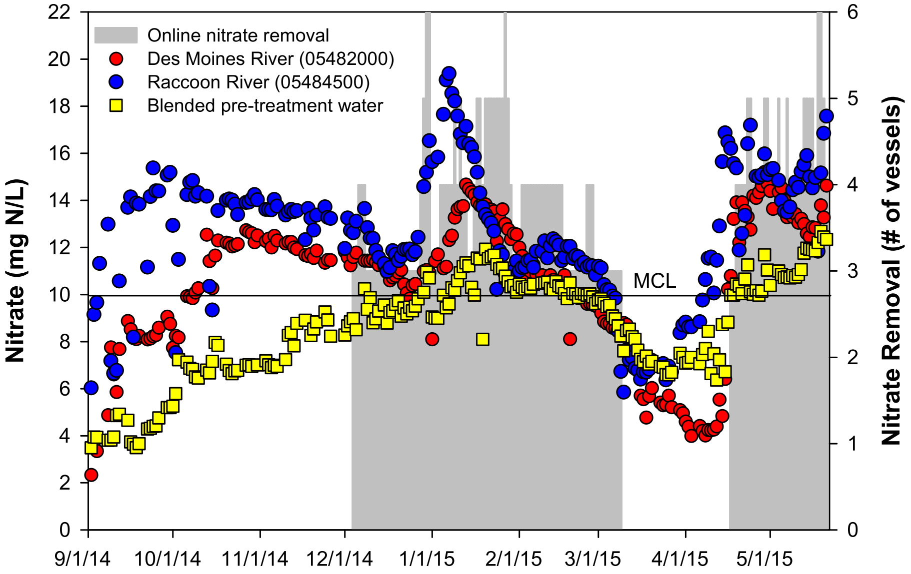

FIGURE 3. Time Series of Nitrate Concentrations in the Raccoon River at Van Meter (USGS Station 05484500) and the Des Moines River at 2nd Avenue (USGS station 05482000) Used by the Des Moines Water Works for Drinking Water Plant Operations. Shaded areas show periods where nitrate removal using ion exchange resins was online and the number of vessels operating at a given time (Jeff Mitchell, Des Moines Water Works, personal communication). Blended pretreatment water is a combination of the two river sources and a third gallery source collecting shallow groundwater. The MCL is the maximum contaminant level for nitrate (as nitrogen, mg/L) allowed in drinking water.

maintained catalog of available sensor datasets, including relevant metadata and parameter measurements; (2) standard services that provide data in a common format using common ontologies; (3) a common geofabric that registers the spatial relationships between important hydrologic features and monitoring points, facilitating the discovery of sensors through upstream, downstream, or other network analyses; and (4) an open marketplace to enable the private sector, including academia, to discover, analyze, and communicate the data in innovative ways.

APPLICATIONS FOR CONTINUOUS NUTRIENT MONITORING

Traditional water quality monitoring can be very costly, especially when time and travel for personnel, specialized field equipment and laboratory analytical costs are factored in. Additionally, data with low spatial and temporal resolution often yield results that are difficult to interpret and may not adequately support management actions. For example, Kirchner *et al.* (2004) illustrated the challenges to interpretation posed by the mismatch between temporal scales on which hydrologic processes (e.g., flow) and water quality parameters (e.g., conductivity) are measured. To best utilize the low temporal resolution data collected by most traditional measurement approaches, scientists and managers have developed statistical modeling techniques to estimate missing concentration or load data from other observations such as discharge, time and season. Despite the recognized potential for bias (Stenback *et al.*, 2011; Hirsch, 2014) and the inherent difficulty in understanding the drivers and fine-scale processes, management policies and actions are increasingly dependent on these model outputs and vulnerable to their uncertainties.

As discussed earlier, *in situ* nutrient sensors offer two fundamental advantages over these traditional discrete sampling approaches: (1) data are collected at a much higher temporal frequency; and (2) data can be disseminated in real time. These improvements present significant opportunities in a number of important applications ranging from real-time decision support to nutrient transport model development. It is important to recognize, however, that the application of continuous nutrient sensors is not without significant costs. For example, a one-time nitrate measurement using a sensor would cost approximately US$60,000 when taking the procurement cost of a sensor ($20,000-25,000) into account along with operation, maintenance, and data validation costs. For comparison, a discrete water quality sample collected and analyzed by the U.S. Geological Survey (USGS) for nutrients costs approximately $4,400 on average (based on 2013 estimates) once salary, equipment, and laboratory analyses are included (Betanzo *et al.*, 2015). However, sensor data will ultimately be less expensive per data point when higher frequency data are needed to quantify storm event responses (Pellerin *et al.*, 2012; Carey *et al.*, 2014), understand stream metabolism (Heffernan and Cohen, 2010; Cohen *et al.*, 2013), and improve the accuracy of nutrient load calculations (Cassidy and Jordan, 2011; Duan *et al.*, 2014; Pellerin *et al.*, 2014; Terrio and Straub, 2015). Cost-benefit analyses should therefore consider the number and temporal density of nutrient measurements needed to describe the process of interest with acceptable accuracy and uncertainty, as well as the added value of data delivery in real time for water management, to determine whether an investment into continuous monitoring is warranted. However, other factors such as the range of parameters to be measured (many of which cannot yet be measured *in situ*) and alternative strategies for intermittent high frequency sampling such as autosamplers should also be considered.

Advancing Our Understanding of Watershed Processes

Watersheds consist of dynamic aquatic environments and the surrounding land from which water drains to a common outlet, and there are many examples of how high frequency data collection benefits the understanding of watershed processes and watershed management. Continuous and real-time streamflow measurements, for example, are critical for supporting flood forecasting and water-resource planning, as well as better understanding hydrology as a driver of water quality (e.g., Hirsch and Costa, 2004). At the watershed-scale, continuous nitrate monitoring is proving useful for both calculating nutrient loading to downstream waters (Pellerin *et al.*, 2014), as well as understanding the drivers of changes in water quality (Hensley *et al.*, 2014). High frequency measurements are also critical to adequately characterize the variability in surface water nitrate and orthophosphate concentrations at some sites, especially during hydrologic events (Pellerin *et al.*, 2012; Bende-Michl *et al.*, 2013; Ferrant *et al.*, 2013; Carey *et al.*, 2014; Outram *et al.*, 2014; Bowes *et al.*, 2015; Sherson *et al.*, 2015) and during periods when instream biological processing or other factors produce, consume, or alter nutrients prior to downstream export (Pellerin *et al.*, 2009; Heffernan and Cohen, 2010; Cohen *et al.*, 2013; Hensley *et al.*, 2014; Snyder and Bowden, 2014). For example, diurnal nitrate patterns similar to those observed in the Potomac River (Figure 2) have been used to estimate rates and drivers of primary productivity in both freshwater (Heffernan and Cohen, 2010; Cohen *et al.*, 2013) and coastal environments (Johnson *et al.*, 2006; Collins *et al.*, 2013). Recent studies have also demonstrated the value of high frequency nitrate sensors for mapping the spatial variability in rivers and lakes (Crawford *et al.*, 2015).

Continuous nutrient monitoring may prove particularly important for assessing and managing nutrient loads delivered across the land-water interface (e.g., edge-of-field). This is particularly true, given the high cost of implementing BMPs to improve or maintain water quality (Sharpley *et al.*, 2006). The high temporal frequency of sensor data provides an opportunity to improve the accuracy and reduce the uncertainty of nutrient load estimates from the edge-of-field. In addition, high frequency data — coupled with weather data and information on land management — may help guide the implementation and evaluation of BMPs at both the field and watershed scales. Finally, high frequency measurements maintained over long periods of time (e.g., years) may also find broad applicability in the development and performance validation of practices that are implemented as part of market-based water quality trading programs (Woodward and Kaiser, 2002; Selman *et al.*, 2009).

Applications of Nutrient Sensors for Coastal Monitoring

Given the importance of nitrogen and phosphorus as drivers of coastal eutrophication (Bricker *et al.*, 2007), hypoxia (Turner *et al.*, 2006), and HABs (Heisler *et al.*, 2008), accurately quantifying the loads of nutrients delivered to coastal environments is critical. Calculating riverine loads to estuaries using continuous sensors offers several advantages over traditional regression-based modeling techniques that rely on infrequent (typically monthly) discrete nitrate data. The higher rate of sampling ensures that dynamics operating across different time scales are captured, thereby largely eliminating bias (Stenback *et al.*, 2011; Hirsch, 2014) and resulting in greater accuracy in concentration and load estimates (Pellerin *et al.*, 2014; Duan *et al.*, 2014; Wild-Allen and Rayner, 2014). This is particularly important when discrete sampling does not fully capture the concentration-discharge (C-Q) range or where the C-Q relationship varies significantly over time. For example, C-Q variability in the Mississippi River basin during years that included a drought (2012) and flood (2013) contributed to differences in nitrate loads using continuous sensor data versus regression-based load estimation models (Figure 4; Pellerin *et al.*, 2014), particularly during spring months critical to the summer formation of Gulf hypoxia. Similarly, calculating loads from high frequency data results in improved precision (Jiang *et al.*, 2014), which enables for more sensitive detection of changes related to basin management and/or climate variability than what is currently possible from models with significantly larger errors or errors that are not quantified.

Improved nutrient load estimates and enhanced coastal monitoring are also needed to better understand the relationship between eutrophication and HABs in coastal waters. Studies suggest the relationships between natural and anthropogenic nutrient loading and the development of HABs in coastal waters are not universal, but rather that site-specific differences in hydrodynamics and environmental and biological controls on phytoplankton growth play an important role in determining where and when HABs will develop (Davidson *et al.* 2014, Anderson *et al.* 2008). However, some of the lack of clear relationship may also be due to methodological limitations and continued reliance on infrequent nutrient concentration measurements to develop these relationships. For example, measured nutrient concentrations and phytoplankton biomass may be negatively correlated at a given point in space and time due to recent incorporation of the nutrient into biomass. As a result, higher frequency estimates of nutrient loads and/or fluxes may instead be better predictors of phytoplankton growth and HAB development (Anderson *et al.* 2008) than infrequently-measured discrete concentrations.

In coastal systems, sensors have also been used to characterize the upwelling of water with high nitrate concentrations and with significant linkages to phytoplankton blooms and HABs. For example, a number of studies have used continuous nitrate sensors in estuaries and coastal waters to better characterize the vertical (Alkire *et al.*, 2010; Johnson *et al.*, 2010) and lateral (Lucas *et al.*, 2011) distribution and transport of nitrate, as well as the impact of nitrate availability on daily changes in primary production (Johnson *et al.*, 2006). Additionally, sensors have been used to estimate nitrate fluxes at high temporal resolution from seafloor sediment (Johnson *et al.*, 2011), to better understand nitrate and orthophosphate transformations at the river-estuarine interface (Gilbert *et al.*, 2013), and to test complex estuarine biogeochemical models (Wild-Allen and Rayner, 2014).

Wastewater and Drinking Water Management

Excess nitrate in drinking water is one of the most acutely harmful effects of nutrient pollution to humans. High nitrate concentrations in drinking water have been linked to a variety of human health effects including birth defects (Brender *et al.*, 2013), methemoglobinemia in infants (Fan and Steinberg, 1996), and cancers (Townsend *et al.*, 2003; Bryan and Loscalzo, 2011). An inventory of all types of public water systems by the U.S. Environmental Protection Agency (USEPA) showed nitrate to be the contaminant that most frequently exceeded a federal drinking water standard among organic and inorganic contaminants (U.S. Environmental Protection Agency, 2005). As a result, nitrate is a regulated contaminant under the Safe Drinking Water Act with a maximum contaminant level (MCL) of 10 mg/L.

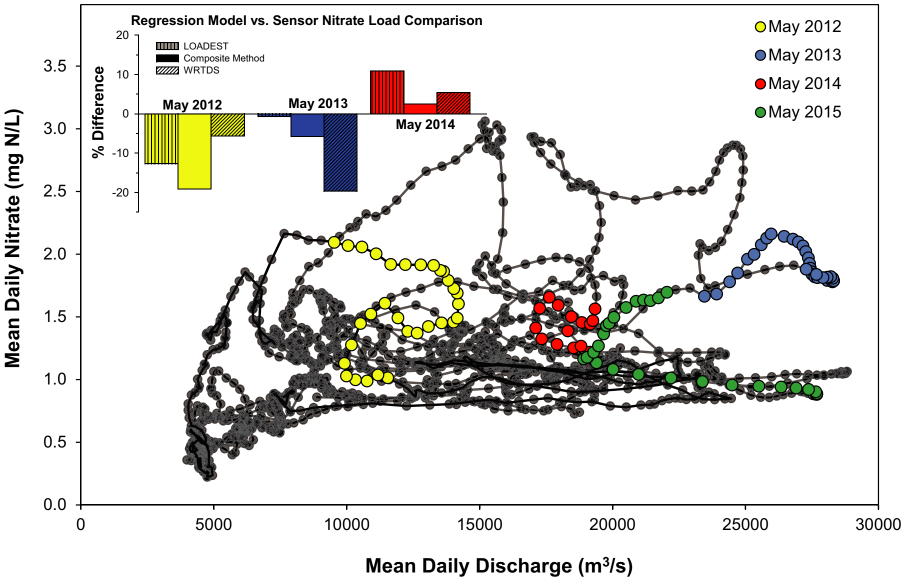

FIGURE 4. Concentration-Discharge (C-Q) Relationships Based on Daily Mean Values for the Mississippi River at Baton Rouge (USGS station 07374000) from November 2011 to May 2015. Daily values for the entire record are shown as grey circles, while daily values during the month of May are colored. Inset shows the percent difference in May nitrate loads during different years from regression-based loads based on the C-Q relationship versus continuous nitrate sensor data (modified from Pellerin *et al.*, 2014).

The ability to rapidly measure nitrate concentrations near drinking water intakes and transmit these data in real time is beneficial for taking management actions, particularly in locations where concentrations approach regulatory limits. For example, nitrate sensor data used by the Des Moines Water Works provides real-time decision support for online nitrate removal (Figure 3), which costs over $7,000 per day to operate (http://www.dmww.com/). Continuous nutrient monitoring also has a history of use in the wastewater industry, allowing for real-time control of processes in treatment plants (Bonastre *et al.*, 2005; Capelo *et al.*, 2007; Drolc and Vrtovšek, 2010). The use of continuous nutrient sensors for monitoring water quality in groundwater is also an area of promising application given that some wells show chemical variability at time scales much shorter than the typical annual cycles for monitoring (Kelly, 1997; Mahler *et al.*, 2011).

THE FUTURE OF NUTRIENT MONITORING

The future of water quality monitoring relies on both traditional discrete sampling approaches and evolving technologies such as remote sensing, wireless applications and *in situ* continuous sensors to answer complex environmental questions. While all of these approaches are important, we have identified three opportunities that will encourage the adoption of affordable, accurate and reliable nutrient sensors. These opportunities address needs for better instrumentation as well as the continued integration of sensor data into sensor networks.

While the focus of this article is on nutrients (and specifically nitrate), opportunities to improve the science and management of water resources with continuous water quality measurements are much broader in scope. For example, regional and national networks of continuous water temperature measurements are being used to assess the implications of climate change on salmonid fish (Isaak *et al.*, 2012) and to aid in stream remediation efforts (Hill *et al.*, 2013). The relative contributions of base flow to surface runoff over large regions have been evaluated using continuous specific conductance data (Sanford *et al.*, 2012; Miller *et al.*, 2014). The analysis of continuous dissolved oxygen, fluorescent dissolved organic matter, turbidity and other parameters across regional and national networks will likely continue to yield new insights into ecosystem processes, watershed hydrology, and constituent transport that are not possible with traditional monitoring approaches.

Opportunity 1: Guiding the Evolution of Sensor Technology

Technological advancements and innovation are leading to rapidly improving sensors and data management tools for environmental monitoring. In the case of nutrient sensors, the increase in freshwater applications has been a primary driver of innovations that ensure high quality data in a variety of challenging matrix conditions (Alliance for Coastal Technologies, 2015). For example, the need to reduce biological fouling of sensors in rivers and streams has spawned a market for chemical and mechanical solutions ranging from copper components to integrated or external wipers. We have identified the following needs as most critical for guiding the evolution of nutrient sensors that are affordable, accurate, and reliable.

Define Instrument Performance Needs. Defining instrument specifications and data quality needs for environmental monitoring from a range of potential users is critical to the evolution of the technology. This is particularly true for nutrient sensors because the varying needs of the intended market result in design tradeoffs that affect the data specifications. For example, UV nitrate sensors developed for wastewater often have lower precision and accuracy than those developed for coastal applications, but they can measure nitrate over a wider concentration range and have greater tolerance for interferences due to shorter path lengths (Pellerin *et al.*, 2013). Defining and communicating instrument performance needs — including those that minimize the lifetime costs of owning and operating the sensors — is critical for future environmental monitoring applications. Open innovation competitions such as the Nutrient Sensor Challenge (www.nutrients-challenge.org) are one mechanism available to help guide sensor development. Indeed, initial activities in the development of the Nutrient Sensor Challenge involved capturing federal and state agency needs for nutrient sensors and these data were used to further inform market research, identify instrument performance targets and design third-party verification testing (Alliance for Coastal Technologies, 2015).

Partnering with Sensor Manufacturers to Develop, Test, and Bring Sensors to Market. Partnerships between federal agencies, states, the research community, and the sensor manufacturers will be critical to bringing sensors, data collection platforms, communications tools and software to market more quickly and at lower cost. This includes providing incentives and support for innovation (e.g., the Nutrient Sensor Challenge) and direct collaboration through formal research and development partnerships between industry and federal, nonfederal, and nongovernmental partners. These partnerships will be critical to addressing future water quality monitoring needs. For example, target reductions in nutrient loading to estuaries such as Chesapeake Bay are often based on total (e.g., particulate plus dissolved) nitrogen and phosphorus (Boesch *et al.*, 2001), yet the current generation of optical and wet chemical nutrient sensors can only directly measure dissolved fractions (nitrate, ammonium, and orthophosphate). To accurately estimate particulate nutrient loads requires turbidity sensors or other *in situ* technology as a proxy for suspended sediment concentrations, coupled with discrete sampling to measure total nutrient concentrations in the suspended sediment. Similarly, "plug-and-play" platforms for sensor integration and mobile software tools for sensor management and data display will continue to be critical to improve the efficiency of deploying and maintaining sensors. Other opportunities exist to work with sensor, data logger, and data management system developers to adopt open standards to facilitate data compatibility.

Opportunities such as the National Oceanic and Atmospheric Administration (NOAA) Ocean Technology Transition Project (http://www.ioos.noaa.gov/marine_sensors/ocean_tech.html) and the USGS Innovation Center for Earth Sciences (http://geography.wr.usgs.gov/ICES/) are fostering the development and application of new sensor technologies to address environmental problems in water. However, there is a need to consider supplemental funding mechanisms that will help to support investments in sensors and water monitoring infrastructure, as well as mechanisms that would enable organizations to collectively purchase, maintain, and utilize information from sensor networks.

Opportunity 2: Develop and Support Monitoring Networks

Environmental monitoring networks are made up of sampling sites that produce comparable data across specific scales of space and time, and have long been recognized as critical to understanding complex environmental processes (Leopold, 1962; Ficke and Hawkinson, 1975). A 2004 report from a presidential commission stated that "The nation needs a coordinated, comprehensive monitoring network that can provide the information necessary for managers to make informed decisions, adapt their actions as needed, and assure effective stewardship of ocean and coastal resources" (U.S. Commission on Ocean Policy, 2004). The report, however, also recognized that no single monitoring design can begin to address or answer all of the nation's water resource issues or questions. Combined with ongoing monitoring networks, a national network of discrete monitoring and continuous nutrient sensors could form a backbone and provide efficiencies in metadata, quality assurance procedures, comparable methodology, and data management that allows readily accessible data storage and retrieval.

There are currently a number of national-scale networks supported by federal agencies and partners, spanning the continuum from satellite monitoring of coastal waters (NOAA CoastWatch, http://coastwatch.noaa.gov/cwn/index.html) to groundwater levels (National Ground-Water Monitoring Network, http://cida.usgs.gov/ngwmn/), all with the goal of providing practical information for policy makers, managers, and the public. National networks for river and stream water quality such as the USGS National Stream Quality Accounting Network (NASQAN, water.usgs.gov/nasqan) were developed to monitor the transport of nutrients and other constituents from large rivers to coastal waters through time (Ficke and Hawkinson, 1975). The NASQAN network relies on relatively low frequency discrete sampling (12-18 samples per year) and modeling techniques for load estimation such as LOADEST (Runkel *et al.*, 2004) to accomplish this goal. The need for continuous water quality monitoring sites in an integrated national network to assess inland and coastal water quality, evaluate changes in nutrient cycling, and protect water resources has been highlighted in several scientific reviews (National Science and Technology Council Committee on Environment and Natural Resources (Subcommittee on Water Availability and Quality), 2007; National Research Council Committee on River Science at the U.S. Geological Survey, 2007).

Building a Core Continuous Monitoring Network. A core continuous nutrient monitoring network should include stable, long-term monitoring sites with a rigorous program of data collection, quality assurance, management, archiving, and synthesis similar to the National Streamflow Information Program (http://water.usgs.gov/nsip/). Such a network would not be independent of a national network of discrete water quality monitoring sites or stream gages, but would instead enhance our ability to answer fundamental questions about the sources, timing, and magnitude of nutrient transport at key locations through the addition of high frequency data. Another important ancillary benefit of such a network is the development of common protocols and data standards by technical experts from federal and state agencies, academia, and industry to support the broader collection of continuous data. For example, the U.S. Integrated Ocean Observing Systems program develops guidance for the Quality Assurance of Real Time Ocean Data

(QARTOD, www.ioos.noaa.gov/qartod/) that are available to the broader community.

The beginnings of such a network are already in place, with the USGS currently operating continuous nitrate sensors at over 100 sites in 24 states (Figure 5). However, many of these sites are funded by cooperators for local studies and are not designed to provide the appropriate spatial context or longevity to answer national — or even regional — scale questions about nutrient transport. Similarly, NOAA currently supports the use of *in situ* sensors for nitrate and orthophosphate at several estuarine sites (e.g., http://neracoos.org/nutrientobservatory), where highly variable conditions make data collection on the appropriate spatiotemporal scales difficult using traditional methods (e.g., Powell, 1995; Stauffer *et al.*, 2014).

While not focused on continuous monitoring, the National Monitoring Network for U.S. Coastal Waters and Tributaries (NMN, http://acwi.gov/monitoring/network/) — designed by the National Water Quality Monitoring Council and more than 80 stakeholders — provides a framework for the expansion of a core network, which would include 258 monitoring sites on freshwater streams and rivers if fully implemented. Building on these efforts, a core network could initially focus on important large rivers, major tributaries, and estuaries where significant investments in discrete sample monitoring have historically been made by federal agencies (Figure 5).

Leveraging the Network. Even though continuous monitoring holds the promise of more cost-effective information per unit of data, it is, like all monitoring, an expensive undertaking. However, the methods, tools, and data developed for a core network would facilitate continuous water quality monitoring by a variety of users and over a broad spatial scale by leveraging resources and expertise. For example, open data standards will lead to increased data sharing which will reduce redundancy and optimize site locations. Industry will see gains in sensor design efficiencies and interoperability, leading to reduced instrument costs. Acceptance and use of common methodologies for sensor operation and maintenance will increase training opportunities. Finally, a national network could lead to efficiencies in acquisition for all users, as entities pool resources to purchase instruments as well as other hardware and software.

A leveraged network of nutrient sensors that builds upon prior investments into methods, tools and infrastructure has the potential to lower costs in a number of ways while filling spatial gaps in the

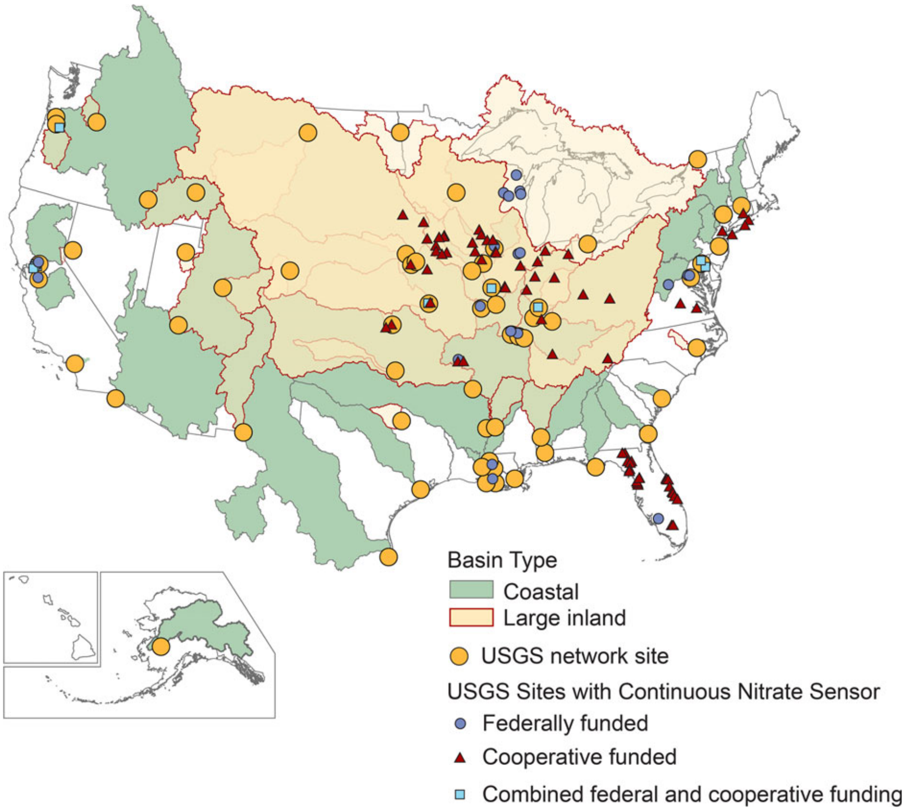

FIGURE 5. Map of Large Coastal and Inland Basins with Discrete Monitoring by the USGS as Part of National Programs (large circles), As Well As Sites with Continuous Nitrate Monitoring Funded by Federal Programs (small blue circles), Cooperator Funding (red triangles), or a Combination of Federal and Cooperator Funding (blue squares).

national landscape. For example, the range of sites in a national network could include drinking water intakes in both surface and groundwater, wastewater discharge monitoring, edge-of-field monitoring, and smaller tributary and stream sites. Organizations that operate and manage these sites might include nongovernmental watershed groups, state agencies, academic researchers, other federal partners, and industry. These new sites, depending on their purpose, could provide information at finer scales, or increase the spatial coverage across the nation.

A number of models for national environmental monitoring networks exist that combine long-term core networks with leveraged sites operated in comparable ways by a variety of entities. One such example is the National Atmospheric Deposition Program (NADP), which is a cooperative effort between various federal, state, tribal, and local agencies, as well as academia, industry, and nongovernmental organizations, to monitor and make available atmospheric chemical deposition data (http://nadp.sws.uiuc.edu/). The NADP includes several smaller networks that follow similar methodologies for the collection and quality assurance of data. A national network of continuous nutrient sensors could operate in a similarly leveraged way to provide broad spatial coverage of comparable data that can be translated into practical information for decision makers and the public.

Opportunity 3: Advancing Integration across Space and Time

An integrated network of nutrient sensors across the country presents a number of new and important opportunities. The information provided by such a network would help assess long-term trends, provide an early warning system to environmental and water quality managers, and enhance evaluations of the effects of management and mitigation actions across multiple scales. To fully realize this potential, however, standardized sensor measurement protocols, data collection strategies, and common quality assurance/quality control (QA/QC) approaches that includes periodic discrete sampling and laboratory analyses of samples will be necessary to develop an inter-calibrated network of *in situ* nutrients sensors with diverse end users. Key to this will be open data standards, incorporated into the sensors and associated hardware by manufacturers, accepted by the water-quality community, and built into data storage hardware and data processing software.

Develop Common Data Standards and Methodologies. In addition to shared methods for the operation and maintenance of sensors, a key need is the identification of data and metadata standards to more effectively manage and share sensor data. Standards should be developed that can work across both water quality and water quantity data types. Another critical need is to provide an index, or catalog, for the registration of datasets by various data producers, and to make those data queryable via common portals. Data management products would conform to the standards identified by the monitoring community, and enable data providers to easily publish their data via an integrated network. Following the concepts outlined in the OWDI, this standards-based catalog and services approach would also tie the sensor locations to a common geofabric (e.g., the National Hydrography Dataset) to allow for queries based on the watershed network (i.e., upstream or downstream). This approach would also allow for these services and catalogs to be accessible by third-party developers who wish to build applications to meet specific use cases and needs.

Improve Data Management and Access. Managing and sharing the data collected from monitoring efforts is critical to preserving the value of those data. The methods used to collect water monitoring data can impact what approaches are taken to store, manage, and publish those data. As part of the data standards development process, the OGC has developed a categorization of water monitoring data types (Table 2). Metadata requirements for each of these different categories of data may differ significantly. For example, the metadata required for a discrete sample (Table 2, data types 1 and 3; i.e., sample collection method, laboratory analytical method, etc.) will differ from the metadata required for a sensor (data types 2 and 4; i.e., deployment period, date last calibrated, etc.). Additionally, the relationship between metadata and reported data can differ greatly for these two types of data: discrete sample data contains a wealth of metadata that describe one or a few results while continuous sensor data requires metadata to describe a sensor that may be associated with multiple results. Because of this difference, the approaches needed to store, manage, and share metadata may be quite different for discrete versus continuous data.

The Water Quality Exchange (WQX) (http://www.epa.gov/storet/wqx) was developed to provide a means for partners to share the monitoring data that they are collecting in a standard format that also allows the data to be documented and understandable by others who are accessing it. Additionally, the WQX standard has enabled USEPA to collaborate with the USGS to develop the Water Quality Portal (Portal; http://waterqualitydata.us), which enables easy access to any water monitoring data collected by USEPA, its partners, or USGS in a standard format. Partially funded by the NMN, the Portal has been tremendously successful, and in 2014 the Agricultural Research Service of the U.S. Department of Agriculture began publishing water quality data from the Sustaining the Earth's Watersheds: Agricultural Research Data System database. Although the Portal has been successful with providing broad access to the discrete sample data, it was never designed to accept and allow sharing of continuous sensor data. Fortunately, data standards have been developed by the OGC that could function as the equivalent of WQX for sensors (http://www.opengeospatial.org/standards/sos and http://www.opengeospatial.org/standards/waterml). A critical component of the current vision is to make the data-sharing capability afforded by the Portal accessible to other federal and nonfederal agencies as well as nongovernmental entities. This is intended to encourage innovation in the private sector that makes the adoption of these standards for new partners as simple as purchasing a new sensor, registering it, and plugging it in.

CONCLUSIONS AND NEXT STEPS

Technology in both sensors and sensor data management has advanced to the point where sensors will become common in water quality monitoring and realize their potential as a critical tool in water quality management. We have therefore identified three specific opportunities for the broader community leadership and that of federal agencies in the next few years that will help accelerate the development and use of nutrient sensors for continuous water quality monitoring. These opportunities include partnerships with industry to develop the next generation of sensors; building sustained and leveraged networks for continuous nutrient and water quality monitoring to inform management and policy solutions; and investing in open data standards and data management protocols that are key to realizing the full benefit of a large-scale, integrated network.

TABLE 2. Broad Categories of Water Observations (Open Geospatial Consortium, http://www.opengeospatial.org/standards/sos).

No	Observation Style	Description
1	*In situ*, fixed observation	Generally temporally dense, spatially sparse, small number of observed phenomena. Examples: river level or stage, river discharge, etc.
2	*In situ*, manual observation	Temporally sparse (e.g., site visits), but potentially spatially dense. Examples: groundwater observations made during pump tests at well sites.
3	*Ex situ*, complex processing observations	Temporally sparse, spatially sparse, many observed phenomena. Examples: nutrients (N, P, etc.), pesticides, biological, etc.
4	Remote-sensed observations	Observations collected by a sensor not in direct contact with the property being observed. These results can be spatially and temporally dense.
5	Complex data products	Processed or synthesized observational data. Examples: output from models, calculations of complex physics-chemistry, biological indices, etc.

Several specific opportunities for partnerships between industry and governmental and nongovernmental organizations are available at present. The Nutrient Sensor Challenge, for example, has presented the monitoring community with an opportunity to provide input that guides the evolution of the technology. Similarly, opportunities exist for innovations in data management, analysis, and visualization with researchers and third party vendors that that can lend expertise in working with the type of "big data" generated by an expanded network. The "Visualizing Nutrients Challenge" (https://www.innocentive.com/ar/challenge/9933113) sponsored by the USEPA, USGS, and Blue Legacy International is yet another example that encouraged the use of open data to create compelling and informative visualizations on nutrient pollution. Workshops that include users as well as third party software manufacturers will provide opportunities for further interaction and collaboration and spur innovation.

Data and metadata standards, and standard data-collection and data-management protocols are critical to realizing the full benefit of a large-scale, integrated network. Key to this will be open and shared data standards that are accepted by the water-quality community and incorporated into the sensors and associated hardware by manufacturers. Shared data standards also make possible common data portals through which stakeholders can make available their data and in turn access additional data in support of their own. This sharing of data will lead to additional collaboration in a self-reinforcing cycle where users discover, for example, data that complement their own and thus allow them to maximize their efforts to fill gaps, minimize duplication, and encourage collaboration across organizations and sectors.

Following an Open Water Data approach for sensors will enable networks to reach their full potential by allowing different parties to share data, particularly along common waterways. It also allows for those data to be integrated with other types of data (i.e., discrete water quality samples, water use data, precipitation data, etc.). As part of OWDI, all of these datasets would also be related to the same stream network, which will allow for other types of queries, such as "Find any sensors downstream of this discharge point", or "Find any sensors, and their corresponding data that are upstream of this drinking water intake." Developing the interoperable sensor networks described here would be a critical component of the OWDI, and also would provide substantial benefit for the water management community and the public.

Because the science of using water quality sensors is still relatively young and many organizations are just beginning to explore the possibilities for monitoring programs, the time is right for innovations that can be utilized and shared. Investments in sensor technologies and data management tools will increase our understanding of the environmental issues as well as the costs/benefits and tradeoffs associated with continuous monitoring. Partnerships between federal and state agencies, nongovernmental organizations, and academic researchers have the ability to effectively leverage investments to build a national network for continuous nutrient and water quality monitoring which will inform management and policy solutions to continue to protect and restore our nation's water resources.

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