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Review article

Synthesizing water quality indicators from standardized geospatial information to remedy water security challenges: A review

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A R T I C L E I N F O

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A B S T R A C T

Water is vital not only for food, energy and sanitation but also for ecosystem functioning, human health, socio-economic progress and poverty reduction. Water security exists when all people have physical and economical access to sufficient, safe, and clean water that meets basic needs. However, water security is threatened by growing human population, episodic environmental disasters, indiscriminate land management practices, contaminants, and escalation in geopolitical conflicts. < 3% of the estimated 1.4 billion cubic kilometers of water on earth is available for consumption. Although there exist a range of laboratory and field methods for measuring the chemical, physical and biological properties of water, the information available to the public remains inconsistent and patchy. To this end, we advance a new theory of a single-value objective water quality index (WQI) that considers the interaction between the above properties, to provide concise information for source water quality surveillance and monitoring. Although geospatial technologies such as remote sensing is credited as a high frequency spatiotemporal mapping tool, exiguous information is available on its application for constructing single-value WQIs. Besides, no remote sensing device exists that directly measures water quality, which must indirectly be inferred through modeling sensed remote sensing signals with measured water properties. This review not only highlights the water security conundrum but also provides an overview of methods for integrating geolocated qualitative (e.g., management data) with quantitative (i.e., measured water constituent properties) into a WQI.

1. Introduction

Other than climate change and the increasing population estimated at 80 million per year, global challenges include indiscriminate land use, rising economic disparities and anticipated deficiencies in food, energy and water (Esteban and Max, 2016; Gleick and Palaniappan, 2010; Lal, 2015b; UNU, 2013). Although water is one of the crucial resources for life on earth, defining a generic water quality standard that satisfies all water uses is challenging. This is because standards considered suitable for human consumption are different from those for industrial or even agricultural use (Haji Gholizadeh et al., 2016; Ritchie et al., 2003). Despite the diverse data processing platforms, water quality determination at field, watershed and even landscape scale is challenging because of spatiotemporal variation in the physical, chemical and biological water constituents (Table 1). Moreover, gleaning water quality information for routine management operations can be impeded by data scarcity and artifacts, nebulous baselines, and validation challenges (de Paul Obade et al., 2013, 2014). Indeed, incoherence in water quality information can contribute to feigned conclusions, poor regulatory enforcement, health risks, or even devalue environmental concerns (EPA, 2016b; Reif, 2011). To avoid catastrophic health ailments, diagnostic screening tools are required to ensure drinking water quality satisfies international standards, specified by World Health Organization (WHO), American Public Health Association (APHA), or Environmental Protection Agency (EPA), among others (EPA, 2016a; Kumar and Puri, 2012; WHO, 2011).

Water pollutants are categorized as point source (PS) and non-point source (NPS). PS pollutants are anthropogenic contaminants discharged via a discrete conveyance thus are traceable to single source (e.g., pipes discharging effluent of industrial or domestic wastewater). In contrast, NPS have diffuse origins, and are facilitated by: (a) infrastructure dysfunction (open/leaky sewer systems, landfill leakages, impervious urban surfaces), (b) land mismanagement (e.g., broadcasting fertilizer on soil surface, flood irrigation, agricultural and livestock waste, soil erosion), meteorological conditions (i.e., precipitation intensity, temperature and wind speed), (c) hydromodification and atmospheric deposition of industrial pollutants (Chipman et al., 2009; Kozlowski et al., 2016; Michalak et al., 2013; Selman et al., 2009; Swanson et al., 2015).

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Table 1
Overview of parameters for water quality surveillance and monitoring.

Physical	Chemical	Biological
Temperature -Water temperature determines the amount of oxygen dissolved in the water, the photosynthesis rate of aquatic plants and metabolism of aquatic organisms. -Causes of temperature change include weather, removal of shading streambank vegetation, impoundments, discharge of cooling water, urban storm water, and groundwater inflows to the stream.	**Chlorophyll** -Chlorophyll pigment is useful for photosynthesis, whereby green plants and algae convert sunlight energy into chemical energy by taking in CO_2, H_2O and producing carbohydrates and O_2. Chlorophyll measures plant and algae pigments, and can be used as proxy biomass estimate. Chlorophyll absorbs blue and red light and reflects green (thus healthy plants appear green). -Algal blooms make water unsuitable for swimming, toxic and unpalatable to the aquatic food chain. Besides, unconsumed algae sink and decay, depleting deeper water of oxygen.	**Benthic macroinvertebrates**: -Macroinvertebrates are organisms large (macro) enough to be seen through the naked eye; and lack a backbone (invertebrate). Benthic refers to the bottom of a waterway. Examples of benthic macroinvertebrates include insects in their larval or nymph form, crayfish, clams, snails, and worms. Most are attached to submerged rocks, logs, and vegetation. -Some macro invertebrates are more sensitive to pollution than others.
pH -pH indicates the alkalinity or acidity of a substance, ranked on a scale from 1 to 14. pH < 7 is acidic whereas pH > 7 is alkaline. A pH of 7.0 is neutral. -Aquatic organisms differ as to the range of pH in which they flourish.	**Suspended solids/minerals** -Suspended minerals or sediments move along in a stream, thus are dependent on water flow and rainfall. -sediments obstruct light and may harbor pathogens. -suspended particles/algae pigments affect how ambient light is absorbed and reflected.	
Streamflow -Streamflow, or discharge, is the volume of water that moves over a designated point over a fixed period of time. -It is affected by weather as it increases during rainstorms and decreases during dry periods; and varies by season.	**Colored Dissolved Organic Carbon** contains fulvic or humic acid, which makes water-bodies to have brownish tan color. Turbidity estimates particulate matter suspended in water. Water with high turbidity is cloudy or opaque. High turbidity increases water temperatures because suspended particles absorb heat, and reduce penetration of light into water. Murky water is unsafe for recreational purposes because hazardous materials/objects are obscured. **Secchi Disk Transparency** measures water clarity. This measurement is done by lowering a black and white disk into the water and recording the depth at which the disk is invisible. Clear water signifies environmental health. **Dissolved Oxygen**: Respiration of most aquatic organisms requires Oxygen dissolved in water. Rapidly moving water dissolves more Oxygen than stagnant water. Colder water dissolves more oxygen than warmer water. -An oxygen-deficient aquatic environment results in water bodies with excess organic material, which cause death to aquatic life.	**Submerged Aquatic Vegetation**: Submerged aquatic vegetation (SAV) provides invaluable benefits to aquatic ecosystems. It not only provides food and shelter to fish and invertebrates but also produces oxygen, traps sediment and absorbs nutrients such as nitrogen and phosphorus. Whereas SAV are dependent upon the transmission of sunlight through the water, the location of individual species depends upon a variety of factors such as salinity, depth and bottom sediment. -plankton include bacteria, archaea, algae, protozoa and drifting or floating animals that inhabit oceans, seas, lakes, ponds

Phosphates which are largely lost through runoff and erosion are major NPS pollutants; compared with nitrates which being soluble are leached and recyclable depending on climate and bioactivity (Causse et al., 2015; de Paul Obade et al., 2013). In essence, high quality soils are natural buffers against contaminants (Adhikari and Hartemink, 2016; Lal, 2018). For brevity, soil organic Carbon (SOC), a proxy of soil quality plays a key role in: (i) water purification and retention, thereby preventing indiscriminately managed nutrients (e.g., nitrogen and phosphorus) from contaminating surface or ground water, (ii) food, fuel, and fibre production, (iii) biodiversity conservation, (iv) climate regulation, and (v) nutrient cycling (de Paul Obade, 2017)

Conceptually, a water quality index (WQI) synthesizes complex water characteristic properties into more interpretable and informative format to support decision-making (Chaturvedi and Bassin, 2010; Khan et al., 2003; Liou et al., 2004; Mohebbi et al., 2013). In essence, WQIs should integrate water quality parameters using techniques that: (i) are simple to develop and use, (ii) correlate well with water constituent properties, and (iii) are replicable and accurate at variable scales (Cobbina et al., 2010; House, 1990; Mohebbi et al., 2013). Although guidelines exist for water quality determination (Ashbolt et al., 2001; WHO, 2011), no universal comprehensive single-value WQI has been conclusively determined. Here, the feasibility of integrating field and remote sensing data to generate a concise objective WQI is explored. Remote sensing technologies acquire data even from inaccessible field locations; is rapid, non-destructive, reproducible, durable and provides both analog and digital data to support automated processing. However, no remote sensing device exists that directly measures water quality, which can instead be indirectly inferred by modeling sensed remote sensing signals with measured water properties. Because, water management decisions determine ecosystem health and productivity, other reviewed priorities include: (i) evaluating consequences of anthropogenic activities on water security, (ii) which strategies ensure sustainable freshwater ecosystems? and (iii) what tools, models, and information are required for cost-effective monitoring of water quality?

2. Risks and impacts of water insecurity

Although 71% of the earth's total surface area (51×10^7 km^2) is water, only 2.5% (3.5 million cubic kilometers out of a total 1.4 billion cubic kilometers) is renewable freshwater (Lal, 2015a). Approximately 70% of this freshwater is contained in ice caps, glaciers, permanent snow, ground ice, permafrost, or ground water, and only 1.2% is available for direct consumption by living organisms (Gleick and Palaniappan, 2010). Consumptive water refers to water unavailable for use after being evapotranspired, ground infiltrated or incorporated into plant or animal tissue, whereas, non-consumptive returns to surface runoff and is reusable after treatment. Blue water refers to fresh surface or ground water and includes precipitation, whereas green water is the soil water, which plants uptake and transpire. “Gray” or contaminated water originates from domestic use, urban and industrial discharge; whereas virtual water encompasses water consumed in production of commodities (e.g., agricultural or industrial) and traded across international boundaries (DIA, 2012; Lal, 2015b).

Water scarcity occurs when human demand or consumption exceeds supply to the extent that per capita availability of renewable freshwater is < 1000 m^3/person/year, whereas water stress or extreme lack of water to satisfy human or ecological demands occurs when water supply < 1700 m^3/person/year (DIA, 2012; Lal, 2015b; Rijsberman, 2006). Globally, an estimated 2 billion people live under squalid conditions in areas of high water stress with limited sanitary facilities, insufficient clean water, and unreliable energy access (WHO, 2008; Water and United Nations, 2008; WHO/UNICEF, 2004). Producing energy requires water, for instance, thermoelectric power expends roughly 40% of freshwater in the U.S. (i.e., 160 billion cubic meters). Yet, water purification and desalinization consumes energy and emits CO_2(g) (FAO, 2008; Rijsberman, 2006; UNDESA, 2014). Reduction in soil-water storage or low soil-water availability at critical crop growth stages can result in pedological, or agronomical drought respectively. Conversely, ecological drought refers to low water availability after land-use conversion, whereas sociological drought occurs when human water demand exceeds supply. Meteorological and hydrological droughts are long-term deficiencies in precipitation or water flow in reservoirs, respectively (Lal, 2013). Imperfections in climate models may explain the sometimes blurred and unreliable information on drought phenomenon (Awange et al., 2016; Cutter et al., 2012). Against the backdrop of abrupt climate change and increasing water footprint, over 50% of the global population will lack clean water, and about 700 million people risk water instigated displacement by 2050 (FAO, 2008; Rijsberman, 2006; UNDESA, 2014).

Societal vulnerability to disasters depends on settlement patterns and population density, economic status, precipitation intensity and land use patterns (Gleick, 2014; Swanson et al., 2015). These disasters can have devastating consequences to human life, environment and even slow down economic progress (Vorosmarty et al., 2000). For instance, flooding destroy infrastructure, displaces people, submerge homes, inundate farmlands, and cause recurring humanitarian crisis in the states of Colorado, Missouri, Illinois, Tennessee, Arkansas, Mississippi, and Louisiana, USA (Coffman and Dobuzinskis, 2013). Not only is the precise environmental footprint of the 2010 gulf of Mexico oil spill unknown, but also the efficacy of remedial measures; especially after spending over US $ 12 billion on the restoration efforts (Haq, 2010). In Africa, disastrous floods recur in the Limpopo basin of Mozambique (Spaliviero et al., 2014), and river Nyando in Kenya (IFRC, 2016). Minimizing disaster impacts requires proactive strategies that include: (a) creating socio economic safety nets, (b) restoration plans backed by scientifically credible data (Bouma and McBratney, 2013; Lal, 2009a, 2009b; Power, 2010). Fig. 1 depicts the interconnection between water quality, society and environment, based on the Driving Forces-Pressure-State-Impact-Response (DPSIR) framework (EEA, 1997). DPSIR gauges effectiveness of strategies for tackling environmental challenges (Gari et al., 2015; Niemeijer and de Groot, 2008).

Demographic explosion and overcrowded settlements, resource over use, poor waste disposal, leaching of pollutants, flooding, dysfunction of infrastructure, and rapid groundwater depletion adversely affect water quality and availability (FAO, 2008, 2013; Laurent and Ruelland, 2011; Mueller-Warrant et al., 2012; Ramadas and Samantaray, 2018; Rijsberman, 2006). Due to water withdrawal for irrigation exceeding average annual recharge, the groundwater levels at Ogallala aquifer declined by 30 cm/year between 1996 and 2011 (i.e., totaling 4.3 m); which doubled to 60 cm/year after the 2012 drought (Kisekka et al., 2017; Lal et al., 2012; NBC, 2016). Meanwhile, the risk of leakages from the $3.8 billion Midwestern U.S. oil pipeline traversing Missouri River not only threatens biodiversity and environmental health but also the sanctity of sacred sites belonging to Native American Indians (Levine, 2016).

As realized from the extreme lead (Pb) levels in Flint, Michigan (USA) in 2016 (Ingraham, 2016), and Toledo, Ohio (USA) in 2010 and 2014 (Lindstrom, 2016; Stewart et al., 2014), no guarantees exist for clean water. Intake of water with elevated Pb levels can cause anemia, severe mental and physical impairment especially in children. Pb *has been used for ages in plumbing fittings and water distribution systems, h*owever, because of Pb poisoning, copper has replaced Pb as a safer alternative. Alternately, chromium-6, a raw material for stainless steel production, was found in approximately 75% of water samples in U.S.A. between 2013 and 2015, and may have been consumed by an estimated 200 million people (Zaremba, 2016). Chromium-6 pollution causes liver damage, reproductive health problems and cancer. Although permissible limit for Pb in treated drinking water is documented as 15 parts per billion (ppb); that for Chromium-6 is unknown (Scott, 2016; Zaremba, 2016). Other adverse ramifications of pollution include soil salinization, and outbreak of water-borne diseases (Rijsberman, 2006; Semenza et al., 2012; Vincent et al., 2004). In Kenya, almost half of the population (~16 million) resides in unhygienic sanitary conditions; which has contributed to disease outbreaks, soaring infant mortality rate, and lower graduation rates among children (http://water.org/country/kenya/). Arsenic, detected in dangerous levels in some drinking water supplies in India (i.e., Ganges delta) and rural China, is carcinogenic and genotoxic in high concentration, and its intake can cause acute abdominal pain, vomiting, diarrhea, muscular pain, and skin cancer (Komorowicz and Barałkiewicz, 2016; Kumar and Puri, 2012). Above all, the arsenic concentration in drinking water should not exceed 10 $\mu g\,L^{-1}$ (WHO, 2011).

Elevated nutrient concentration (i.e., Total Nitrogen (TN) or Total Phosphorus (TP)) in water reservoirs trigger blossoming of cyanobacteria such as *Anabaena* sp., *Planktothrix* or *Microcystis* sp. that cause eutrophication. Eutrophication stresses aquatic ecosystems, reduces water aesthetics impacting on tourism industry, threatens drinking water supplies, produces a bad odor, and clogs reservoirs (de Paul Obade et al., 2013, 2014; Vincent et al., 2004). According to the World Health Organization, the maximum threshold for phytoplankton *microcystin* toxin in recreational waters is 20 μg/L (Michalak et al., 2013). Water contaminated with toxic cyanobacterium can cause ailments such as blue baby syndrome (*methaemoglobinaemia*), liver cancer, nausea, vomiting, respiratory illnesses or even death (Chang et al., 2015; Wright, 2016). Extreme cases of “hypoxia” or “dead zones” attributed to oxygen depletion have reportedly occurred in the Black Sea (Eastern Europe), Lake Taihu and Pearl River Delta (China), Lake Winnipeg (Canada), Lake Erie, the Gulf of Mexico, and Chesapeake Bay (U.S.) (Selman et al., 2009). Elsewhere, the water hyacinth (*Eichhornia crassipes*) invaded Lake Victoria, the largest lake in East Africa with over 30 million people in its vicinity, blocking fishing access and providing breeding grounds for disease carrying mosquitoes and snails (le Roux et al., 2016; UNEP, 2013).

Geopolitical tensions are simmering between Ethiopia and Egypt because of the grand renaissance dam, located in the Blue Nile river (Khaled et al., 2016). This dam built at an estimated cost of U.S. $4 billion has a capacity to retain about 70 billion cubic meters of water, useful for irrigation, flood control, and generating 6000 MW of electricity. However, apart from Egypt risking the loss of 60% of its croplands due to water diversion, the environmental consequences could be catastrophic (Chellaney, 2013; Khaled et al., 2016). Alternately, Turkey's numerous dam construction along the Tigris and Euphrates river basin for military purposes, hydroelectric power and irrigation, has reduced water flow and created rifts with neighboring Iraq and Syria (Gleick, 2014). Syria accuses Turkey of socio-economic sabotage and creating a humanitarian crisis by contaminating water with fecal matter, a scenario that enhances risk of waterborne diseases, lowers yields of irrigated fruits and vegetables, and interferes with aquatic ecosystems (Chellaney, 2013). Drought may have ignited the ongoing civil war in Syria, that has created a humanitarian crisis and displaced

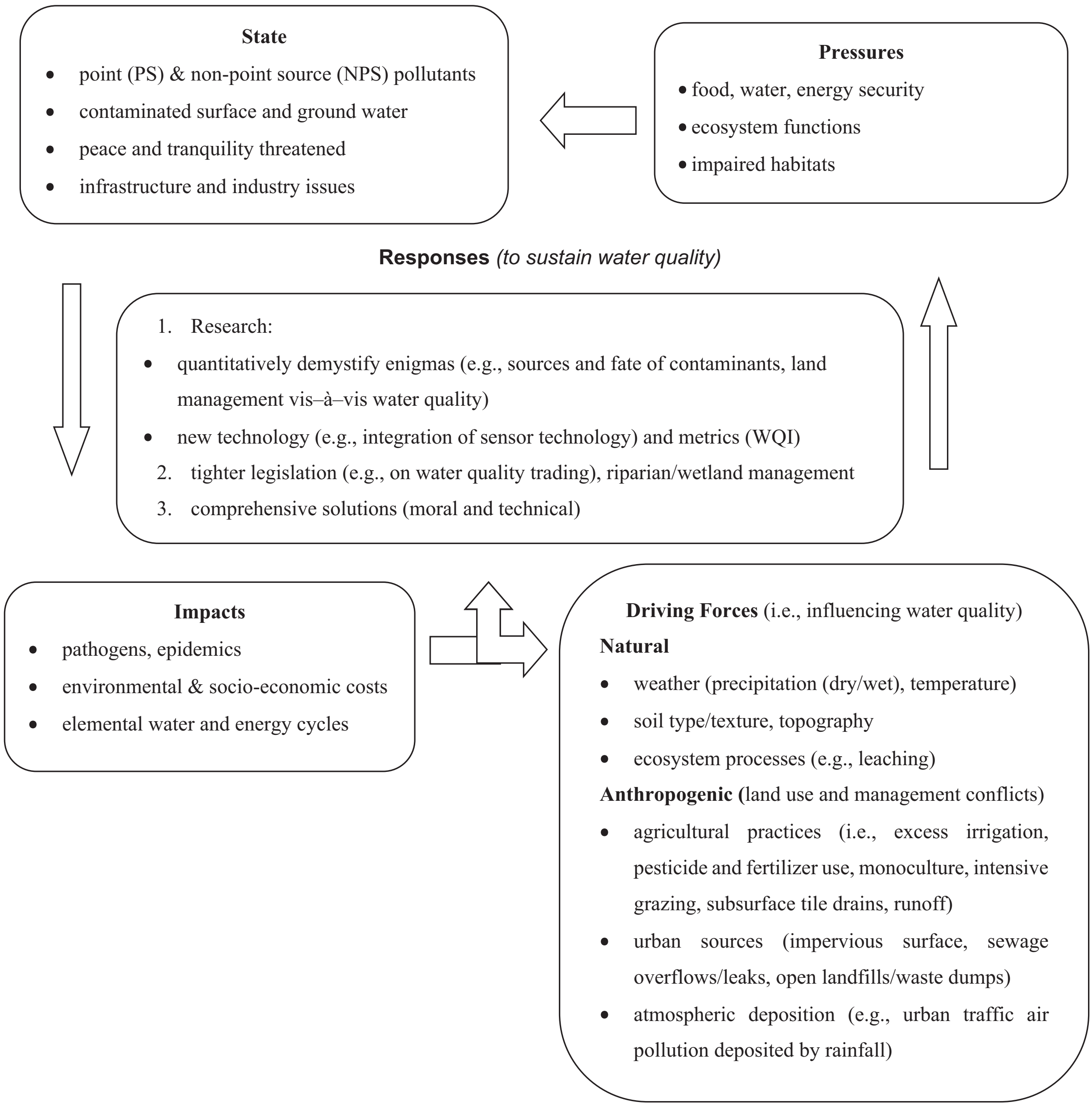

Fig. 1. Driving Forces-Pressures-State-Impact-Responses (DPSIR) water quality infrastructure. Abbreviation WQI stands for Water Quality Indicator.

over 2 million people (Gleick, 2014).

3. Remediation options overview

Despite existing legislation, the complexity of natural systems and their interactions with anthropogenic activities complicate prioritization of remediation strategies to control pollution. Curtailing water pollution requires understanding of key driving forces influencing water quality, strict enforcement mechanisms, and proactive management strategies. Examples of feasible management options include the Proper Functioning Condition (PFC) assessment method and water quality trading (WQT). PFC method evaluates the hydrology, vegetation and erosion/deposition within riparian areas thereby providing critical information for understanding the drivers of ecosystem function (Kozlowski et al., 2016; Swanson et al., 2015). However, PFC is a subjective approach because the assessment criteria relies on expert opinion and visual interpretation of field sites either directly, or by using raw aerial photographs and satellite imagery. Besides, PFC does not objectively integrate qualitative and quantitative water quality constituent variables, and thus is non-comprehensive and unreliable. In this regard, the question remains how to blend data on water properties into a credible and robust water quality metric? Otherwise, WQT is a market strategy designed to reduce water pollution through issuing permits and providing economic incentives to support ecosystem management and restoration initiatives.

Approximately half of water reservoirs within USA do not meet minimum water quality standards (EPA, 2000). Purifying polluted water resources in USA is estimated to cost millions of dollars each year (de Paul Obade et al., 2013; Ritchie et al., 2003). The Clean Water Act (CWA) was enacted in 1972 to: (i) control water effluent standards by establishing a pollution cap based on mandated Total Maximum Daily Loads (TMDLs), (ii) ensure the water reservoirs are fishable and swimmable (EPA, 2016b; Freeman, 2000; Ghosh et al., 2011). Based on the sum of all pollutants, TMDLs provide permissible pollution limits allowable in water reservoirs. Under section 303 (d) of CWA, all impaired waters within respective watersheds must be listed (EPA, 2016b). Although CWA is credited for significantly controlling PS water pollutants, NPS pollution remains a problem.

As a strategy to control pollution, the U.S. federal CWA requires all facilities that discharge wastewater, or storm water within specific watersheds to purchase a WQT permit applicable within the defined jurisdiction. WQT allows point polluters (e.g., industries) to opt out from fully implementing pollution reduction technologies but instead purchase "pollution credits" from NPS polluters (e.g., farmers) (de Paul Obade et al., 2014; Moore, 2014). However, prior to participating in WQT, U.S. Environmental Protection Agency (EPA) requires these NPS polluters to incorporate best management practices (BMPs). Examples of BMPs include crop rotation, water conservation, allocating a conservation easement, prescribed burning, grazing management plan, conservation agriculture, recycling waste, integrated nutrient and pest management (Kozlowski et al., 2016; Lal, 2013; Lal et al., 2012; Swanson et al., 2015).

WQT permits are issued by the National Pollutant Discharge Elimination System (NPDES) a subsidiary of EPA, which enforces the CWA mandate (Ghosh et al., 2011; Moore, 2014; Stephenson and Shabman, 2011). Approximately 1000 permits have been issued costing between US $ 400 to 2000. However, NPDES continues to impose stringent measures for WQT permits, for instance, by reducing TP limits to 1 mg/L, with considerations of lowering further to between 0.5 and 0.75 mg/L, which is arduous to monitor (de Paul Obade et al., 2014; Moore, 2013). No wander, specifying spatial and temporal scales for which WQT can be most effective remains a challenge.

To recapitulate, WQT credibility depends on: (i) enforcement of a pollution cap, (ii) BMP verification system, and (iii) restrictions curtailing pollution (de Paul Obade et al., 2014; EPA, 2016b; Savard, 2000; Shrestha et al., 2008). WQT can be a risky venture because legal liability is not transferrable for credits purchased, implying that the credit buyer may be fined for exceeding TMDL cap stated in original permit should the contract with the non-point polluter lapse (Selman et al., 2009). The Alpine and Muskingum WQT programs (Moore, 2014); and the electrical power research institute's (EPRI), exemplify WQT initiatives operational in Ohio, Kentucky and Indiana (USA) (EPRI, 2016), that can be emulated in other localities.

4. Monitoring water quality strategies

Sustainable water quality management entails: (i) developing robust water quality assessment models and tools, and (ii) utilizing technologies that can promote water use efficiency, for instance, by increasing green water, purifying gray water and minimizing virtual water (de Paul Obade et al., 2013, 2014; Lal, 2015a; Maruthi Sridhar and Vincent, 2007; Mohammed, 2002). Besides, new monitoring capabilities providing real time information are required to assess the risks and implications of anthropogenic land management practices on water reservoirs (Bushaw-Newton and Seller, 1999; Vincent et al., 2004). Many different statistical methods, automated or semi-automated technologies utilizing field data, and interpretations from aerial or satellite imagery, or both to assay water quality exist (Hajigholizadeh and Melesse, 2017). A conceptual flow chart portraying a holistic yet synthesized WQI is depicted in Fig. 2.

Water quality information is gleaned by a range of techniques varying in complexity and sophistication. The most commonly used methods regardless of limitations include: (i) *in situ* (local/point/field) measurements (e.g., Secchi disk depth (SDD) which evaluates the depth of water transparency/clarity in reservoirs but may be limited for flowing river systems), (ii) laboratory analyzed samples, and (iii) empirical/analytical modeling of remotely sensed data from scanned locations or samples (Haji Gholizadeh et al., 2016; Maruthi Sridhar and Vincent, 2007; Olmanson et al., 2013; Reif, 2011). Although lacking in spatial coverage and temporal extent, adequately collected field data for a point is accurate, and thus used to validate data from other sources, such as remote sensing. However, collecting field data is a time-consuming, labor intensive process, and thus expensive (Ramesh et al., 2010; Ritchie et al., 2003).

From a practical standpoint, laboratory analyzed field data and geospatial technology (e.g., remote sensing and Global Positioning Systems (GPS)) are integrated using a Geographical Information Systems (GIS) (Fig. 3) to provide spatially/temporal continuous data that can be validated and complemented from the sampled field points (Gitelson et al., 2008; Haji Gholizadeh et al., 2016; Ritchie et al., 2003). GIS are computer-based tools that integrate database operations and can query, statistically analyze, overlay, visualize, manage and store geographically referenced data. The GIS-based Soil and Water Assessment Tool (SWAT) driven largely by weather data approximates surface runoff, discharge, sediment and nutrient loads and can thus be used to predict agricultural management impacts on water quality (Ha et al., 2018; Michalak et al., 2013). Other hydrologic and water quality models include the ADAPT, ANNAGNPS, APEX, COUPMODEL, CREAMS/GLEAMS, DRAINMOD, EPIC, HYDRUS, HSPF, InVEST, KINEROS2/AGWA, MACRO, MIKE SHE, MT3DMS, RZWQM2, SHAW, SWIM3, STANMOD, TOUGH, WARMF etc. (Adhikari and Hartemink, 2016; Kisekka et al., 2017; Yuan et al., 2015). Among the parameters integrated and analyzed by these models include hydraulic conductivity, TN, TP, pesticide concentration, bacteria loading rate, evapotranspiration (ET), soil porosity and erodibility, soil bulk density (ρ_b), fecal coliform concentration, soil organic carbon (SOC), runoff curve number, rooting depth, crop yield, subsurface drainage flow etc., (Adhikari and Hartemink, 2016; Kisekka et al., 2017; Yuan et al., 2015). However, none of these models explicitly generate "single-value" WQI. Table 2 reviews standardized WQIs that have been utilized with mixed results (Mohebbi et al., 2013; Ramesh et al., 2010).

4.1. Water quality surveillance and monitoring using remote sensing

Determination of the spatial extent of water resources is not a difficult task at a specific site; the problem is monitoring water quality. This knowledge gap is a major impediment in the process of planning or even informing water resource managers and decision makers on the socio-economic impacts of development projects. Thus, the potential of technologies such as remote sensing which provide continuous spatial and temporal data needs to be fully explored to understand water quality dynamics. Optical, thermal, active and passive remote sensing based systems that are either hand-held, or operated from boats, aircraft, and satellites have transformed the paradigm of mapping by sensing beyond the visible electromagnetic spectrum and providing repetitive, spatially continuous data in real-time that can be upscaled or downscaled (de Paul Obade and Lal, 2013; Oliver and Webster, 2014; Ouma, 2016; Pérez Hoyos et al., 2016; Roy et al., 2008, 2014). Active systems emit and detect own energy to and from the target, whereas passive systems rely on energy from the sun. Unlike passive sensors, active sensors generate pulses that penetrate clouds and smoke. Although remote sensing systems provide frequent synoptic coverage, and are non-destructive, its caveats include: (a) bidirectional reflectance distribution function (BRDF) effects and spectral mixing problem caused by adjacency effects and uneven illumination, (b) data-gaps attributed to cloud cover, smoke, sun-glint, aerosols, atmospheric interference; all of which lower the signal-to-noise ratio (SNR), (c) rigorous and continuously evolving data processing and calibration requirements (e.g., changes in data quality and formats following the launching of newer satellites), (d) mismatches between spatial, spectral and temporal resolution, (e) high costs of data acquisition, archiving and absence of long-term data (Chang et al., 2015; de Paul Obade et al., 2013). Haze in imagery attributed to variation in sensor slope angles or directions can be minimized by ratio-ing sensor bands. Notwithstanding, the explosion of digital geo-information products create redundant information (Ouma, 2016; Vitharana et al., 2008).

Although an overview is provided here on water quality sensors (Tables 3, 4, & 5); the sensor specifications, other sundry details such as

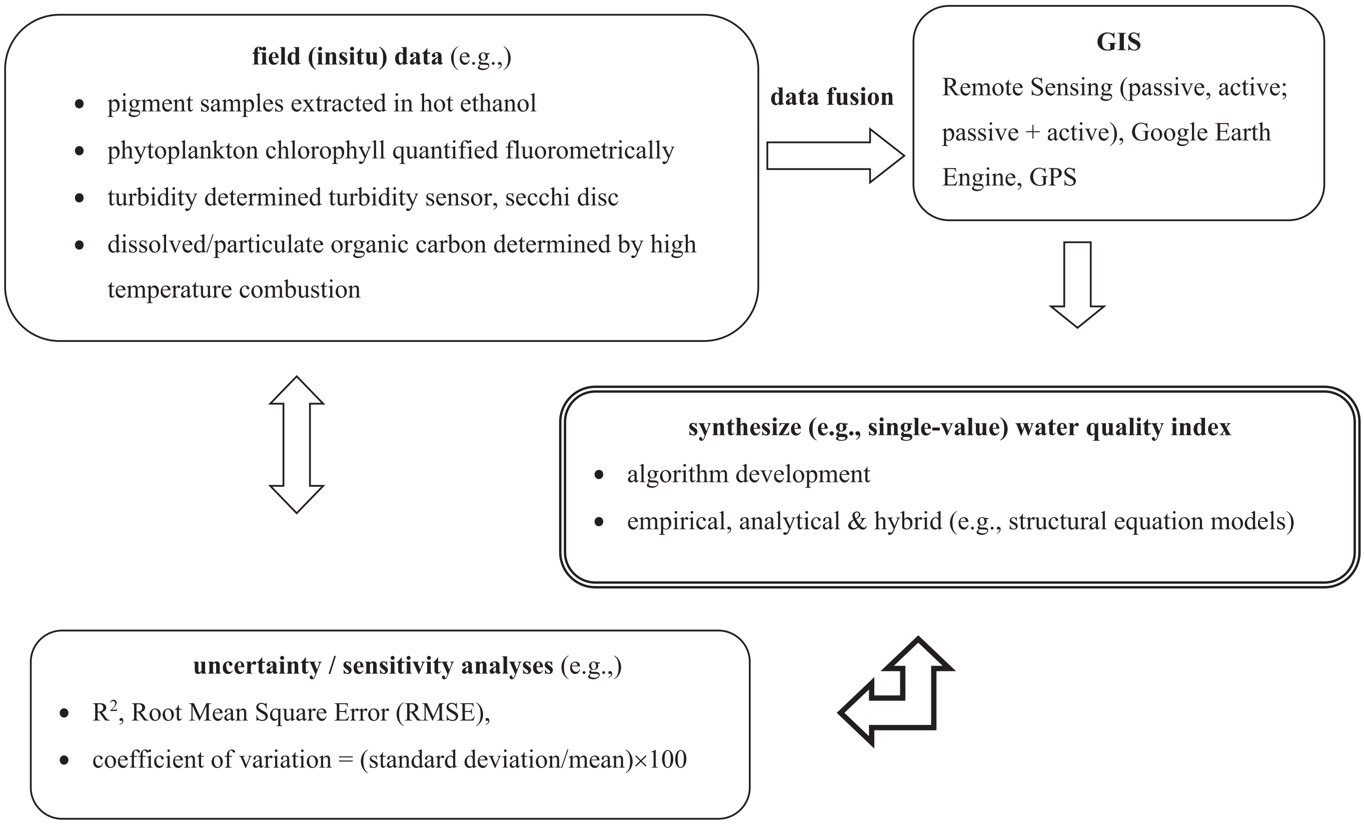

Fig. 2. Framework for monitoring water quality. Passive Sensors rely on naturally occurring external energy source (e.g., sun for illumination), whereas Active sensors provide own energy source to scan target.
Abbreviations: GIS, Geographical Information Systems; GPS, Global Positioning Systems.

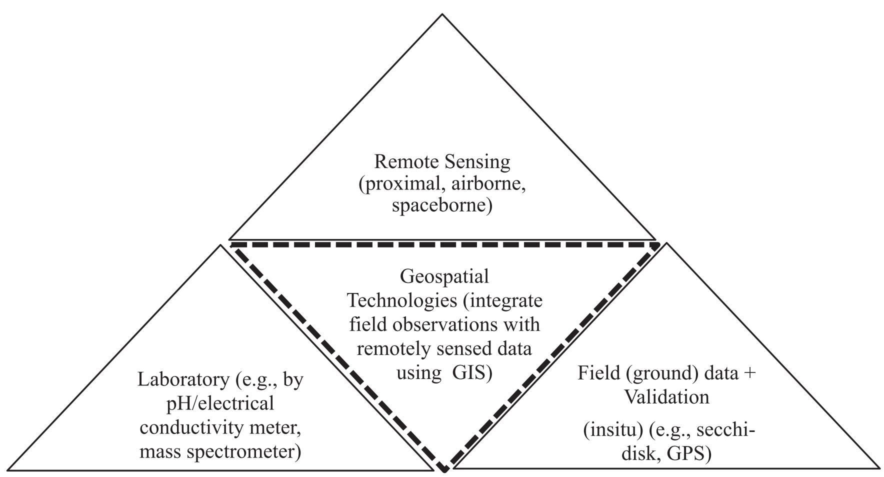

Fig. 3. The system-based approach to Water Quality determination.
Abbreviations: GIS: Geographic Information Systems; GPS: Global Positioning Systems.

software's, digital processing techniques are beyond the scope of this work, but are accessible online or from the following references (Chang et al., 2015; de Paul Obade and Lal, 2013; Haji Gholizadeh et al., 2016; Hajigholizadeh, 2016; Ouma, 2016; Pérez Hoyos et al., 2016; Revilla-Romero et al., 2016). Prior knowledge of spatial (pixel size, or size of smallest feature distinguishable by sensor), spectral (band ranges, or region of electromagnetic spectrum sensed), temporal (frequency of imagery acquisitions), radiometric (color depth, or number of digital levels representing data) resolution, and swath (area of coverage) are important considerations in sensor selection (Ouma, 2016). Notably, remotely sensed data should be calibrated to ensure highest data quality that accurately represents measured surface signals. Atmospheric signal attenuation and geometric distortions are assumed miniscule in proximal sensing given the reduced atmospheric path length and proximity to target of measurement. However, data acquired from aerial/space platforms have substantial path length, necessitating geometric and radiometric corrections. Radiometric correction minimizes atmospheric distortions thereby enhancing clarity of imagery, whereas geometric correction compensates for systematic and random errors necessary for accurate extraction of distance, area and direction information from imagery (Chang et al., 2015).

Spaceborne sensors may be of high spatial resolution (e.g., Compact

Table 2
Some standardized water quality index (WQI) (adapted from Mohebbi et al., 2013).

Index	Method	Parameters	Advantages	Disadvantages
(1) NSFWQI (U.S. National Sanitation Foundation Water Quality Index)	-Selects and aggregates product of the respective weighted water quality parameters, -uses rating curves ranging from 0 to 100 with zero denoting poor quality and 100 high water quality	unique parameters i.e., dissolved oxygen, fecal coliforms, pH, biochemical oxygen demand, nitrate, total phosphate, temperature change, turbidity, total solids	estimates water quality	-inflexible structure, -non-comprehensive input parameters, -subjective rating curves
(2) Drinking Water Quality Index (DWQI)	*4 definite steps*: -parameter selection and categorization, -development of sub-index with regression statistics -assignment of weight factors to parameters, -final aggregation of DWQI with Min-Max operator	22 parameters i.e., <u>Acceptability parameters</u>: Aluminum (Al), Ammonia nitrogen, Calcium (Ca^{2+}), Chloride (Cl^-), Hardness (total), Iron (Fe), Magnesium (Mg^{2+}), pH, Sodium (Na^+), Sulphate (SO_4^{2-}), Total dissolved solids (TDS), Zinc (Zn). <u>Health – based parameters</u>: Arsenic (As), Cadmium (Cd), Turbidity, Copper (Cu), Fecal coliforms, Fluoride (F^-), Lead (Pb), Manganese (Mn), Mercury (Hg), Nitrate (NO_3^-) and Nitrite (NO_2^-)	Simple, and stable for estimating water quality	-complex and time consuming calculation, -subjective rating curves, -lack of flexibility in selection of water quality parameters and evaluation criteria
(3) Canadian Drinking Water Quality Index (DWQI)	Compares observed water quality parameters to standard or guideline values considered benchmarks rather than standardizing observations using subjective rating curves	flexible	-simple calculations, -flexibility in selection of water quality benchmarks and parameters	-insensitive score system i.e., equal effect of different water quality parameters in final DWQI score

Airborne Spectrographic Imager (CASI) and HyMap hyperspectral, QuickBird, IKONOS, and SPOT-5/HRG), medium (e.g., Landsat), or coarse resolution with limited spectral range (e.g., National Oceanic and Atmospheric Administration (NOAA) which is a consortium of several coarse resolution sensors) (Table 3) (Chang et al., 2015; Haji Gholizadeh et al., 2016; Hajigholizadeh, 2016; Pérez Hoyos et al., 2016; Reif, 2011; Revilla-Romero et al., 2016). Aerial sensors operating from relatively lower platforms (altitude) have greater spectral and spatial resolution but less swath width (Table 4) (Olmanson et al., 2013). Because hyperspectral sensors have numerous, narrower, spectral bands, they contain more precise and detailed information than multispectral and panchromatic respectively; but require greater storage and processing requirements (Chang et al., 2015; Haji Gholizadeh et al., 2016). Data from coarse spatial resolution satellite sensors are generally lower in cost and sometimes free, compared with high spatial resolution satellite or aerial sensors (Chipman et al., 2009; Vinciková et al., 2015). Besides, airborne surveys require more flight planning, and adjustment considerations to cater for air traffic, solar conditions, weather and flight dynamics (i.e., pitch, roll, yaw) (Chang et al., 2015; Chipman et al., 2009; Reif, 2011). Data acquired using ground based sensors such as portable hand-held spectroradiometers (e.g., Fieldspec,[1] PSR+ 3500[2]) can be used to calibrate or even synergize data from space or aerial platforms (de Paul Obade et al., 2013; Maruthi Sridhar and Vincent, 2007).

Oftentimes relating remotely sensed spectra to specific water properties can be challenging. In general, the criteria used to decipher information from remotely sensed data include color, pattern, texture and tone. Gleaning water quality information from remotely sensed data initially requires correlating sensed signals (e.g., reflectance, brightness temperature because water has low emissivity, backscatter) directly recorded or available in spectral libraries to surrogate *in situ* measured variables such as total sediments (or turbidity), algae concentrations (~chlorophyll-a), particulate and/or dissolved organic matter (PDOM), temperature, dissolved oxygen, salinity, total phosphorus (TP), total nitrogen (TN), chlorides, fecal coli bacteria, transparency (e.g., Secchi disk depth), or pH (Chipman et al., 2009; Ramadas and Samantaray, 2018; Ritchie et al., 2003). Basically, clear water generates higher reflectance within the blue region of the visible electromagnetic spectrum than in the red, and vice versa for turbid water.

Moderate Resolution Imaging Spectrometer (MODIS) sensor on the Aqua satellite, Landsat, and Earth Observing-1 (EO-1) satellite data have been used to model the relationship between surface reflectance, chlorophyll-a, and water hyacinth presence (le Roux et al., 2016). Awange et al. (2008a, 2008b) demonstrated using Gravity Recovery and Climate Experiment (GRACE) and auxiliary data that abrupt climate change and not the expanded hydroelectric power station in Uganda significantly contributed to the receding Lake Victoria water level. At a coarse spatial resolution (i.e., 300–400 km), GRACE satellite maps temporal variations of the Earth's gravitational field which highly correlates with terrestrial water storage after screening-out atmospheric and oceanic effects (Pérez Hoyos et al., 2016). Aircraft-mounted thermal sensors, Advanced Very High Resolution Radiometer (AVHRR) or other satellite platforms, not only permit mapping of thermal plumes but may also provide new insights on the role oceans play in regulating weather (Ritchie et al., 2003). Alternately, thermal pollution arising from extreme water temperature variability attributed to thermal releases from electrical power plants, adversely affect aquatic ecosystem. Indeed, high water temperatures kill aquatic life because essential gases (e.g., oxygen) are released from the water into the atmosphere (Kumar and Puri, 2012). Although temperatures of surface water bodies significantly fluctuate on a seasonal or even daily basis, that for

[1] http://www.asdi.com/products-and-services/fieldspec-spectroradiometers/fieldspec-4-hi-res

[2] http://www.spectralevolution.com/spectroradiometer_PSR_plus.html

Table 3
Some current spaceborne water quality systems (Modified from Hajigholizadeh, 2016; Chang et al., 2015).

Satellite sensor	Spectral bands (wavelength, nm)	Spatial resolution (m)	Approximate revisit interval (days)	Category
OrbView-2 SeaWiFS	8 (402–885)	1130	16	Coarse (regional – global)
Envisat-1 MERIS	15 (390–1040)	300–1200	daily	
Terra MODIS	2 (620–876)-5 (459–2155)-29 (405–877 & thermal band)	250, 500, 1000	1 to 2	
EO-1 Hyperion	242 (350–2570)	30	16	Moderate resolution
Landsat-8 OLI/TIRS	5 (430–880)-1 Pan (500–680)-2SWIR (1570–2290)-1cirrus cloud detection (1360–1380)-2TIRS (10600–12,510)	30, 15, 100	16	
HICO	128 (350–1080)	100	10	
Digital Globe Quickbird	4 (430–918)-1 Pan (450–900)	2.62–0.65	2 and half	High resolution
SPOT-5 HRG	3 (500–890)-1 Pan (480–710)-1SWIR (1580–1750)	2.5; 5–10–20	2 to 3	
CARTOSAT	Pan (500–850)	2.5	5	

groundwater is relatively stable (Pérez Hoyos et al., 2016). Active sensor Radar data such as the synthetic aperture radar (SARs) are useful for mapping oil spills in water bodies, ocean topography and for regional ice monitoring (Chang et al., 2015; Haji Gholizadeh et al., 2016; Minvielle et al., 2015).

Different inversion methods, for instance, empirical (e.g., statistical), analytical (bio-optical) and hybrid (i.e., empirical and analytical combined) are frequently used to extract water quality information from remotely sensed data; sensed from specific bands, and transformed into indices (Chang et al., 2015; Gitelson et al., 2008; Ramadas and Samantaray, 2018). Remote sensing indices are numerical indicators derived from ratios of spectral bands that highly correlate with specific object of interest. Empirical methods are site specific and non-transferable, whereas analytical methods based on the correlation between optical information and the radiative transfer equation are transferable (Reif, 2011; Ritchie et al., 2003). However, generic analytical models are yet to be constructed with data from hyperspectral bands (Chang et al., 2015). Mapping using remotely sensed data entails preprocessing and classification techniques such as supervised and unsupervised, which utilize statistical algorithms to discriminate among groups. Major preprocessing steps especially critical in change detection and time-series analyses include georeferencing, radiometric calibration, atmospheric corrections and cloud removal (Pérez Hoyos et al., 2016). Classifying digital imagery can be useful for making predictions and interpolation. Common classification techniques include: (i) cluster analyses, which group data based on similarities within classes, or dissimilarities of different classes, (ii) structural equation models (e.g., multivariate regression, least squares optimization, factor analyses, and discriminant analysis or supervised pattern recognition technique that uses linear combinations of several variables to construct statistical classification of sample into categorical-dependent values, and (iv) geostatistics (de Paul Obade and Lal, 2013; Larson and Pierce, 1994).

It is desirable to develop a standardized objective single-value WQI that rates water quality based on specific use on a % scale, ranging from zero to 100 with for instance, 100% denoting high/excellent quality and 0% poor quality water (Abtahi et al., 2015). Ascertaining high and low quality water thresholds a priori is critical for generating a standardized framework to ease comparability between WQIs values. Hypothetically, utilization of electromagnetic radiation to monitor water quality is feasible because backscattering characteristics of water is dependent on the type and concentration of substances in water. Thus,

Table 5
Some current microwave radiometers for water quality studies (Hajigholizadeh, 2016).

Satellite	Spatial resolution (km)	Swath width (km)	Frequency (GHz)
Nimbus-5	25	3000	19.4
TRMM	8 × 6 at 85.5 GHz to 72 × 43 at 10.7 GHz	760	10.7,19.4,21.3,37.0, & 85.5
SEASAT	22 at 37.1 GHz to 100 at 6.6 GHz	600	6.6, 10.7, 18.0, 21.0, and 37.1

WQI can be constructed from measured water quality constituents (e.g., Table 1) sensed over a broad electromagnetic spectrum, for instance, by screening key variables using factor analyses in tandem with multiple regression methods to analyze the interrelationship between measured and latent critical variables. Eq. (1) exemplifies WQI parameters, which can subsequently be graphed as WQI (y-axis) over time (x-axis) to depict spatial-temporal trends:

$$\begin{aligned} \mathrm{WQI} \equiv \{ & \text{weather (e. g., precipitation, temperature, wind speed)} \\ & + \text{land use and management (e. g., fertilizer} \\ & \text{/manure application and tillage practiced)} \\ & + \text{remotely sensed data (spectral library acquired at different time} \\ & \text{/location)} + \text{water constituent properties (i. e.} \\ & \text{, clarity, pesticides, bacteria, nutrient loading)} \\ & + \textit{others} \text{ (e. g.} \\ & \text{, assumed baseline, reservoir circulation} \\ & \text{, residence time for water constituents)} \} \end{aligned} \tag{1}$$

WQI represents water quality index

Applicable parametric multivariate regression methods that synthesize complex models include the: (i) forward selection which selects predictor variables sequentially until the model fit (R^2) cannot be improved, (ii) backward elimination or reverse of forward selection, or (iii) stepwise method which deletes one non-significant predictor variables upon each iteration. However, parametric statistics must satisfy the following assumptions: (i) independence of observations, (ii) linearity, (iii) homoscedasticity, and (iv) normal distribution of errors

Table 4
Some current Airborne Water Quality Sensors (modified from Hajigholizadeh, 2016).

Sensor	Scan system/sensor type	Number of bands, & spectral range (μm)	Resolution (m)	Imaging swath
Airborne Visible Infrared Imaging Spectrometer (AVIRIS)	Whiskbroom/Hyperspectral	224 (0.40–2.50 μm)	17	12 km (614 pixels/scanline)
Daedalus Multispectral Scanner (MSS)	Pushbroom/Multispectral	12 (0.42–14.00 μm)	25	714 pixels/scanline
PROBE-1 in USA (HyMap)	Whiskbroom/Hyperspectral	128 (0.40–2.50 μm)	3 to 10	512 pixels

(Chong and Jun, 2005; Hajigholizadeh and Melesse, 2017; Mehmood et al., 2012). In contrast, non-parametric methods such as artificial neural networks (ANNs), support vector machines (SVMs), genetic algorithms (GAs), decision tree techniques, principal component analyses (PCA), partial least squares regression (PLSR) are parsimonious (Hajigholizadeh and Melesse, 2017; Liou et al., 2004). Multivariate statistics not only screen significant model variables but can also extract regression coefficients even from quantitative and qualitative (e.g., management) data simultaneously, which can conjoined as exemplified in de Paul Obade and Lal, (2016). In principle, the construction of a Soil Quality Index (SQI) and WQI are similar, because both constitute chemical, physical and biologic attributes. Eq. (2) is a prototype water quality model subsequently aggregated, standardized and transformed into WQI (%) (Eq. (3)). For monitoring purposes or to conduct relative comparison of water quality which is the gist of WQIs, the units cancel out so long as "oranges are compared with oranges", that is, same input variables (e.g., physical, chemical and biologic properties) are modelled into WQI per site.

$$\text{Attribute Index (AI)} \propto \{\text{water properties (e. g.}, \text{clarity, nutrient concentration.....)}\} \tag{2}$$

$$\left(\mathrm{WQI} = {}^{AI}\!\big/_{MAXAI - MINAI}\right) \times 100 \tag{3}$$

AI: Attribute Index computed from derived remote sensing band ratios.

MAXAI: Maximum Aggregate Index remotely sensed for good quality water (e.g., good drinking water per WHO standards).

MINAI: Minimum Aggregate Index remotely sensed for poor quality water (e.g., waste-water).

Other techniques include the parsimonious decision tree which recursively splits data into mutually exclusive subsets using tree like partitions, and classifies data either continuously or categorically (discretely) (de Paul Obade et al., 2014; Saghebian et al., 2014). Yet, the challenge remains identifying specific spectral resolution sensitive to water constituents to rank and map critical parameters influencing water quality. Nonetheless, the multivariate regression models and geostatistics may facilitate interpolation and mapping of point data over a continuous surface, especially through fusing field data with remotely sensed data.

5. Calibration and validation

Although uncertainty and sensitivity analyses (SA) are often carried out in tandem, they serve different purposes; because uncertainty focuses on error propagation, whereas SA explores the strength of relationships between model inputs and outputs (Yuan et al., 2015). SA is applied in parameter fixation, screening-out of key model parameters, resource allocation for parameter and data measurement, model or algorithm corroboration, and to justify scientific based decisions (Hajigholizadeh and Melesse, 2017; Yuan et al., 2015). However, SA results of models are derived for specific scenarios thus are site and condition dependent. For all applications, the reliability of geo-information products depends on sampling strategy; accuracy between model inputs, outputs and actual field conditions. Among the common sampling techniques for field data acquisition include; random, cluster, stratified, systematic, and Latin hypercube among others. Visual inspection of statistical input versus output plots (e.g., box and whisker plots) can rudimentarily inform on model reliability.

Frequently used "goodness-of-fit-measures" for quantifying accuracy include: (i) coefficient of determination (R^2), which describes the closeness of data to the fitted regression line, (ii) standard deviation, and (ii) root-mean square error (RMSE). For instance, a lower RMSE signifies higher accuracy, and conversely for R^2. $R^2 > 0.7$ is considered as the limit of applicability for linear regression-based sensitivity techniques (Yuan et al., 2015). Cross validation is another accuracy assessment technique whereby each measured observation is sequentially estimated and error determined (de Paul Obade and Lal, 2013; Mehmood et al., 2011, 2012). Confusion matrix or classification table is normally used to evaluate accuracy of remotely sensed data (Hajigholizadeh and Melesse, 2017). This table has rows representing observed categories of the dependents, the columns having predicted categories for each dependent, whereas the diagonal representing perfect predictions. Thus, the percentage of correct classifications is computed based on relating the diagonal values with the totals in the row or columns, using Kappa. Kappa (KHAT statistic) is a metric that quantifies the difference between actual and chance (Congalton, 1991; Hajigholizadeh and Melesse, 2017). Kappa values range between negative to positive one, with positive one value indicating a perfect classification significantly better than a random result, whereas negative values represent a poor classification (Congalton, 1991; de Paul Obade et al., 2014; Foody, 2002, 2010).

6. Conclusions and future perspectives

This review highlights water security issues and explicates potential requirements for constructing a synthesized WQI linking biogeochemical water properties to refined remotely sensed data. Indeed, water quality is determined by quantifying concentration or existence of specific biological, chemical and physical water constituent properties. However, constituent elements that can threaten water quality do change over time (i.e., sometimes high concentration of Arsenic occur). Thus, this review proposes a WQI generated from fused field and remotely sensed data that can integrate multivariate qualitative and quantitative water constituent properties into a "single-value" WQI, so insights can be gained to guide future model development and applications. WQI information is pertinent for (i) decision making and management especially regarding control and remediation of contamination hotspots, (ii) reporting and understanding various water quality threats to human health, and (iii) surveillance of water quality life cycle, for instance, from the reservoir to tap.

Some future remote sensing systems equal to this task are also listed in Table 6. It is important to note that small payload sensors are becoming fashionable because their electronics and detection sensors have reduced size and mass (Ouma, 2016). For instance, unmanned aerial vehicles (drones), or nanosatellites (e.g., from Terra Bella[3] and Planet Labs[4]) packed with high-powered optics and sensors are not only affordable in comparison to current aerial and space borne sensors, but their agility allows them to achieve attitude-change maneuvers rapidly allowing them to operate from any orbit; thereby providing high temporal resolution products (Olmanson et al., 2013; Ouma, 2016; Rango et al., 2009).

From a practical standpoint, calibrated remote sensors/devices synonymous to "no contact thermometers" should be constructed that directly measure water quality (e.g., in %, with 100% denoting excellent/high quality and 0% low quality). Such devices will not only provide an insight on the deviation from pristine conditions for natural water bodies (e.g., to inform recreational water users); but also enhance knowledge on the interrelationship between water quality dynamics, abrupt climatic change and anthropogenic land use/management. Thus, robust algorithms accurately synthesizing water quality information and transferable to other regions are required. Finally, development of high fidelity and concise WQI will be useful for time series analyses so as to enhance the understanding of socio-economic dynamics vis–à–vis water quality status.

[3] https://terrabella.google.com/?s=in-action&c=case-mongolia

[4] https://www.planet.com/

Table 6
Future water quality observation systems.

Sensor	Swath width	Spatial resolution (m)	Spectral channels & resolution (nm)	Temporal resolution (days)	Application	Launch year	Reference
Sentinel-2A (European Space Agency)	290 km	10 m (4 visible and near-infrared bands), 20 m (6 red-edge/shortwave-infrared bands (SWIR)) & 60 m (3 atmospheric correction bands)	Multispectral imager (MSI) 13 spectral bands (443 nm–2190 nm)	5	Chlorophyll, Harmful algal blooms (HABs), turbidity, water content indices	23rd June 2015 Operational 7 years	1
Sentinel-2B/2C	● monitor ocean conditions, topography, pollution, currents.					2017/2021	1,4
Sentinel-3A	● monitor impact of climate changes on melting ice, ocean temperature					2016	2,4
Sentinel-3B, 3C, 3D, 4	● improve meteorological forecasts					Before 2021 Operate for 7 years	2
Environmental Mapping and Analysis Programme (EnMAP)	30 km	30 × 30 m	spectral range from 420 nm to 1000 nm (VNIR) and from 900 nm to 2450 nm (SWIR) Hyperspectral; Visible to SWIR	4	-assess spatial and temporal water scarcity and water quality problems? -how climate change, intensive agriculture, water demanding industries and high population density affect water availability? -how water quality is impacted by land use change and climate?	2018 and operate for 5 years	4
Hyperspectral InfraRed Imager (HyspIRI)	instruments on low orbit	60 m @nadir	visible to short wave infrared (VSWIR: 380 nm–2500 nm) in 10 nm bands and a multispectral 3 to 12 µm in the mid and thermal infrared (TIR)	VSWIR = 19 TIR = 5	-water quality -surface temperature maps -Evapotranspiration (ET). -drought	not assigned ~ 2016	3
GeoEye-2		0.25				2016	4
Plankton, Aerosol, Cloud, ocean Ecosystem (PACE)						http://pace.gsfc.nasa.gov	
Web-based decision support systems			simple and streamlined to enhance data accessibility to end-users and decision makers				4
Google Earth Engine can be used to create cloud free mosaics					https://earthengine.google.com/		

1. http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2/Facts_and_figures
2. http://space.skyrocket.de/doc_sdat/sentinel-3.htm
3. https://hyspiri.jpl.nasa.gov/.
4. Additional sensor information available also in Chang et al., 2015; Haji Gholizadeh et al., 2016; Ouma, 2016.

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