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Editorial

Water Quality Modeling and Monitoring

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This Special Issue, "Water Quality Modeling and Monitoring", comprises 19 papers. Water quality in watersheds and waterbodies is a critical issue due to its direct influence on public health, the biological integrity of natural resources, and the economy. Anthropogenic pollution of rivers is a challenge for many countries, and many programs and policies directed at pollution reduction have been set up, implemented, or are currently being implemented in many watersheds. Juwana et al. [1] evaluated water quality programs aiming to achieve pollution reduction through uncertainty and sensitivity analysis of the Citarum River, Indonesia. They explored Monte Carlo simulations to analyze parameter uncertainty and sensitivity, contributing to the program's effectiveness. The water quality parameters cadmium, biochemical oxygen demand (BOD), and fecal coliform were the most affected [1]. Their uncertainty and sensitivity analyses demonstrated that the most effective programs for improving the pollution index were domestic waste, farming, solid waste, and water resource programs [1].

Field water sample collection has been traditionally used to monitor water quality parameters, as in studies by Schussler et al. [2] and Gilliam et al. [3]. Remote sensing technology with large-scale synchronous observations in the Pearl River Delta in China have also been used to effectively monitor total nitrogen (TN) [4]; however, TN is a non-optically active substance, so it is difficult to retrieve TN through analysis methods. TN was retrieved based on Landsat8 images of the Pearl River Delta using a statistical method (stepwise regression). The proposed method performed well with a small mean absolute error (MAE) (0.36 mg/L for TN) and high agreement (R^2 = 0.61 for TN) between the in situ data and the retrieval concentration [4]. Water quality parameters in the Nile Delta's coastal and inland waters, such as chlorophyll-a (Chl-a), total suspended matter, and chromophoric dissolved organic matter, were retrieved by analyzing data from three satellite sources: the Sentinel-3 Ocean Land Color Imager (OLCI), Sentinel-2A Multispectral Instrument (MSI), and Landsat-8 Operational Land Imager (OLI) [5].

Water quality monitoring not only deals with conventional parameters, e.g., total suspended solids (TSS) or turbidity in sediment basins [2] and pH, dissolved oxygen, and specific conductivity in a coastal stream [3], but also trace elements, including Al, Cr, Mn, Fe, Co, Ni, Cu, Zn, As, Cd, Sn, Cs, Tl, Pb, Th, and U [6], and emerging organic contaminants, such as endocrine disruptor compounds (EDCs) [7]. Water quality monitoring has been conducted in rivers [3,6], estuaries [7], and groundwater wells [8] as well as an urban stormwater infiltration trench (low-impact development) in South Korea [9] and a water supply distribution system [10]. After the physicochemical parameters (ammonia, nitrates, nitrites, and phosphates) were evaluated, seventeen EDCs, including estrogen, phytoestrogen, sitosterol, and banned industrial pollutants, were studied at ten sites of the Douro River estuary, Portugal, in 2019, with a 97% detection frequency on average [7]. Water quality data frequently suffer from missing records and/or short-gauged monitoring/sampling sites. Some statistical regression techniques (e.g., ordinary least-squares regression) are

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used to substitute missing values or to extend records at short-gauged sites. Trous-based record extension techniques for water quality data were evaluated by Anwar et al. [11].

Advanced models or modeling methods also allow researchers, engineers, and managers to better understand water quality dynamics and spatial distributions in watersheds and waterbodies that discrete data collections or monitoring cannot reveal. Point and non-point source pollutant fluxes including chemical oxygen demand (COD), biochemical oxygen demand (BOD_5), total dissolved solids (TDS), TN, nitrate and nitrite–nitrogen (NOx-N), total phosphorous (TP), and phosphate (PO_4-P) were estimated by integrating several models in the Lake Hawassa watershed in Ethiopia's Rift Valley Basin [12]. The integration of HEC-GeoHMS and SCS-CN with the catchment area enabled the stormwater pollution load of Hawassa to be determined [12]. Advances in machine learning techniques can serve practical water management needs such as salinity level estimation in California's Sacramento-San Joaquin Delta [13]. Machine learning algorithms were used for biophysical classification of Lithuanian Lakes based on remote sensing data [14]. Traditionally, water quality is evaluated using field data collection with laboratory analysis and statistical procedures, making real-time monitoring ineffective. When water pollution is a severe issue, forecasting water quality to control water pollution and informing consumers in the event of the detection of poor water quality is crucial. Water quality index (WQI) classification models based on machine learning were developed for the Langat River Basin in Malaysia [15] to forecast the WQI as a way to enhance water quality management. These machine learning models include deep learning techniques such as multilayer perceptron (MLP) and long short-term memory (LSTM) networks in a multitask learning framework [13]; six supervised machine learning algorithms (e.g., logistic regression, support vector machines (SVM)) to classify biophysical conditions (clear, moderate, Chla-dominated, and turbid) for 357 lakes and ponds in Lithuania [14]; and artificial neural networks (ANNs), decision trees (DTs), and SVM to classify river water quality [15]. Both water quantity and quality within a mixed-land-use catchment were simulated for peri-urban streams in Sjaelland, Denmark, using the data-driven system dynamics (SD) model (the visual object-oriented software Stella Architect) [16]. The SD model developed is a scalable, combined hydrologic and in-stream water quality model that can simulate dissolved oxygen, temperature, nitrate, ammonium/ammonia, soluble reactive phosphorus, and chlorophyll-a [16].

The suitability of groundwater for drinking and irrigation was studied using water quality indices, GIS methods, and the partial least-squares regression model for 59 groundwater wells in Makkah Al-Mukarramah Province, Saudi Arabia [8]. The potential risk of pesticide leaching in edaphoclimatically suitable areas for coffee cultivation in Espírito Santo state, Brazil, was evaluated using the groundwater ubiquity score, leaching index, and attenuation factor/retardation factor (AF/RF) methods [17]. Green algae play an important role in ecosystems as primary producers, but they can cause algal blooms. Reducing algal blooms through dam operation without using additional water resources was modeled with the Environmental Fluid Dynamics Code—National Institute of Environment Research (EFDC-NIER) model calibrated for the Namhan River, South Korea [18]. The oscillation flow produced a significant variance in flow velocity, leading to a 20–30% reduction in algal bloom density in the Namhan River through the operation of the Chungju Dam [18].

The transport of substances with pollutants in flowing water systems is, in principle, the result of advection and dispersion (longitudinal and transverse). Pollution transport via longitudinal dispersion was experimentally studied for low flow conditions in sewer systems with a sediment layer in pipes [19]. At a low discharge rate, deposited sediment on the pipe bottom changed the hydraulic roughness and magnitude of the dispersion coefficient at low Reynolds numbers (close to the laminar flow), but water quality models often assume turbulent flow. An approximation equation to estimate the dimensionless dispersion coefficient was developed as a function of the Reynolds number, sediment thickness, and pipe diameter [19].

To prevent the discharge of polluted stormwater offsite and mitigate the downstream effects on the water quality of the receiving waterbody, stormwater regulations in the USA require erosion and sediment control practices to be implemented during construction. Schussler, Perez, Whitman, and Cetin [2] implemented a field monitoring program on two in-channel sediment basins along Highway U.S. 30 construction sites in Tama County, Iowa, USA, using automated water samplers to study sediment concentrations at the inflow and discharge of the basins to quantify sediment removal efficiency. Sediment basins are typically employed on the edge of disturbed watersheds to capture and detain suspended sediment from stormwater runoff by providing residence time and storage to promote gravitational settling. The limited right-of-way in the construction site led to the creation of in-channel basins from existing roadside channels to treat stormwater [2]. Inflow turbidities in the monitored sediment basins reached magnitudes of up to 103 NTU, and discharge turbidity monitoring indicated negligible turbidity reduction or even turbidity increase on several occasions. Throughout the study, they recommended [2] several potential design improvements and techniques (e.g., implementing an upstream forebay, geotextile lining, baffles, floating surface skimmer, and flocculant dosing) to enhance in-channel sediment basin performance.

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