


Monitoring, Modeling and Management of Water Quality

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Abstract: In this special issue, we are able to present a selection of high-level contributions showing the manifold aspects of the monitoring, modeling, and management of water quality. Monitoring aspects range from cyanobacteria in water using spectrophotometry via wide-area water quality monitoring and exploiting unmanned surface vehicles, to using sentinel-2 satellites for the near-real-time evaluation of catastrophic floods. Modeling ranges from small scale approaches by deriving a Bayesian network for assessing the retention efficacy of riparian buffer zones, to national scales with a modification of the MONERIS (Modeling Nutrient Emissions in River Systems) nutrient emission model for a lowland country. Management is specifically addressed by lessons learned from the long-term management of a large (re)constructed wetland and the support of river basin management planning in the Danube River Basin.

Keywords: effectiveness of measures; scenarios and forecasts; socioeconomic context; sources and pathways of water pollution; system understanding; water governance; water quality statuses and trends; water pollution control



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1. Introduction

Different types of pressures, such as nutrients [1], micropollutants [2], microbes [3], nanoparticles [4], microplastics [5], and antibiotic-resistant genes [6], endanger the quality of water bodies. Evidence-based pollution control needs to be built on the three basic elements of water governance: Monitoring, modeling, and management [7]. Monitoring sets the empirical basis by providing space- and time-dependent information on substance concentrations and loads, as well as driving boundary conditions for assessing water quality trends, water quality statuses, and providing necessary information for the calibration and validation of models [2,7]. Modeling needs proper system understanding and helps to derive information for times and locations where no monitoring is done or possible. Possible applications are risk assessment for the exceedance of quality standards, assessment of the regionalized relevance of sources and pathways of pollution, effectiveness of measures, bundles of measures or policies, and assessment of future developments as scenarios or forecasts [8]. Management relies on this information and translates it in a socioeconomic context into specific plans for implementation [9]. The evaluation of the success of management plans again includes well-defined monitoring strategies [7]. This special issue provides an important overview of a hot topic in this context as it is summarized in the following.

2. Issue Contents

2.1. Monitoring

In order to measure the chromaticity of water and the content of dissolved matter more accurately, effectively, and cheaply, a chromaticity measurement system based on the image method was proposed and applied by Cao et al. [10]. The measurement system used a designed acquisition device and image processing software to obtain the red-green-blue (RGB) values of the image and converted the color image from RGB color space to hue-saturation-intensity (HSI) space to separate the chromaticity and brightness. According

to the definition of chromaticity, the hue (H), saturation (S) values, and chromaticity of standard chromaticity solution images were fitted by a non-linear surface, and a three-dimensional chromaticity measurement model was established based on the H and S values of water images. For the measurement of a standard chromaticity solution, the proposed method has a higher accuracy than spectrophotometry. For actual water sample measurements, there is no significant difference between the results of the tested method and the common spectrophotometer method. This verified the validity of the chromaticity method. In addition, the system was tested for measuring the concentration of ammonia nitrogen, phosphate, and chloride in water, with satisfactory results [10].

Management of cyanobacteria blooms and their negative impact on human and ecosystem health requires effective tools for monitoring their concentration in water bodies. Agberien et al. [11] investigated the potential of derivative spectrophotometry for the detection and monitoring of cyanobacteria using toxigenic and non-toxigenic strains of *Microcystis aeruginosa*. *Microcystis aeruginosa* was quantified in deionized water and surface water using traditional spectrophotometry and the first derivative of absorbance. The first derivative of absorbance was effective in improving the signal of traditional spectrophotometry; however, it was not adequate for differentiating between signal and noise at low concentrations. Savitzky–Golay coefficients for the first derivative were used to smooth the derivative spectra and improve the correlation between concentration and noise at low concentrations. Derivative spectrophotometry improved the detection limit by as much as eight times in deionized water and as much as four times in surface water. The lowest detection limit measured in surface water with traditional spectrophotometry was 392,982 cells/mL, while the Savitzky–Golay first derivative of absorbance was 90,231 cells/mL. The method provided herein provides a promising tool for the real-time monitoring of cyanobacteria concentration [11].

Water environment pollution is an acute problem, especially in developing countries, so water quality monitoring is crucial for water protection. Cao et al. [12] developed an intelligent three-dimensional wide-area water quality monitoring and online analysis system. The proposed system was composed of an automatic cruise intelligent unmanned surface vehicle (USV), a water quality monitoring system (WQMS), and a water quality analysis algorithm. An automatic positioning cruising system was constructed for the USV. The WQMS consists of a series of low-power water quality detecting sensors and a lifting device that can collect the water quality monitoring data at different water depths. These data are analyzed by the proposed water quality analysis algorithm based on the ensemble learning method to estimate the water quality level. Then, a real experiment was conducted in a lake to verify the feasibility of the proposed design. The experimental results obtained in a real application demonstrated the good performance and feasibility of the proposed monitoring system [12].

Flooding is among the most common natural disasters in our planet and one of the main causes of economic and human life loss worldwide. Evidence suggests an increase in floods at a European scale, with the Mediterranean coast being critically vulnerable to this risk. The devastating event in the West Mediterranean during the second week of September 2019 is a clear case of this risk, when a record-breaking flood (locally called the “Cold Drop” (Gota Fría)) was swollen into a catastrophe in the southeast of Spain and surpassing previous all-time records [13]. By using a straightforward approach with the Sentinel-2 twin satellites from the Copernicus Programme and the ACOLITE atmospheric correction processor, Caballero et al. [13] accomplished an initial approximation of the delineated flooded zones, including agricultural and urban areas, in quasi-real-time. This robust and flexible approach requires no ancillary data for rapid implementation. A composite of pre- and post-flood images was obtained to identify changes and mask water pixels. Sentinel-2 identifies not only impacts on land but also on water ecosystems and their services, providing information on water quality deterioration and the concentration of suspended matter in highly sensitive environments. Subsequent water quality deterioration occurred in large portions of Mar Menor, the largest coastal lagoon in the Mediterranean.

This study demonstrated the potentials brought by the free and open-data policy of Sentinel-2, a valuable source of rapid synoptic spatio-temporal information at a local or regional scale for supporting scientists, managers, stakeholders, and society in general during and after an emergency [13].

2.2. Monitoring and Modeling

The increasing deterioration of aquatic environments has attracted more attention to water quality monitoring techniques, with most researchers focusing on the acquisition and assessment of water quality data, but seldom on the discovery and tracing of pollution sources. In the study of Wang et al. [14], a semantic-enhanced modeling method for ontology modeling and rules building is proposed, which can be used for river water quality monitoring and relevant data observation processing. The observational process ontology (OPO) method can describe the semantic properties of water resources and observation data. In addition, it can provide the semantic relevance among the different concepts involved in the observational process of water quality monitoring. A pollution alert can be achieved using the reasoning rules of the water quality monitoring stations. In this study, a case is made for the usability testing of the OPO models and reasoning rules by using a water quality monitoring system. The system contributes to the water quality observational monitoring process and traces the source of pollutants using sensors, observation data, process models, and observation products that users can access in a timely manner [14].

Urban river catchments face multiple water quality challenges that threaten the biodiversity of riverine habitats and the flow of ecosystem services. Medupin et al. [15] examined two water quality challenges: runoff from increasingly impervious land covers, and effluent from combined sewer overflows, within a temperate zone river catchment in Greater Manchester, North-West UK. Sub-catchment areas of the River Medlock were delineated from digital elevation models using a Geographical Information System. By combining flow accumulation and high-resolution land cover data within each sub-catchment and water quality measurements at five sampling points along the river, they identified which land cover(s) are key drivers of water quality. Impervious land covers increased downstream and were associated with higher runoff and poorer water quality. Of the impervious covers, transportation networks had the highest runoff ratios and therefore the greatest potential to convey contaminants to the river. We suggest more integrated management of imperviousness to address water quality and flood risk, while urban well-being could be achieved working with greater catchment partnerships [15].

Hepp and Zessner [16] present a simple mapping key suitable for quick and systematic assessments of the type of agricultural and civil engineering structures present in a certain agricultural catchment, as well as the impact they may have on the spatial distribution of critical source areas. An application of this mapping key to three small sub-catchments of a case study catchment, with an area of several hundred square kilometers (one-stage cluster sampling), in Austria clearly revealed that road embankments with subsurface drainage can exert a major influence on the emission and transport pathways of sediment-bound pollutants such as particulate phosphorus (PP). Due to this, the semi-empirical, spatially distributed PhosFate model is extended to separately model PP emissions into surface waters via storm drains along road embankments. Furthermore, the overall share of road embankments with subsurface drainage on all road embankments in the case study catchment was inferred with the help of a Bayesian hierarchical model. The combination of the results of these two models showed that the share of storm drains at road embankments on total PP emissions ranges from about one fifth to one third in the investigated area [16].

Water quality in urban streams is highly influenced by emissions from waste water treatment plants (WWTP) and from sewer systems, particularly by overflows from combined systems. During storm events, this causes random fluctuations in discharge and pollutant concentrations over a wide area. The study by Dittmer et al. [17] focuses on the environmental impact of micropollutant loads emitted from combined sewer systems. For

this purpose, high-resolution time series of river concentrations were generated by combining a detailed calibrated model of a sewer system with the measured discharge of a small natural river to a virtual urban catchment. This river base flow represents the remains of the natural hydrological system in the urban catchment. River concentrations downstream of the outlets were simulated based on mixing ratios of base flow, WWTP effluent, and CSO discharge. The results showed that the standard method of time proportional sampling of rivers does not capture the risk of critical stress on aquatic organisms. The ratio between average and peak concentrations and the duration of elevated concentrations strongly depends on the source and the properties of the particular substance. The design of sampling surveys and evaluation of data should consider these characteristics and account for their effects [17].

Bayesian networks (BN) have increasingly been applied in water management but not to estimate the efficacy of riparian buffer zones (RBZ). The methodical study of Gericke et al. [18] aims at evaluating the first BN for predicting RBZ efficacy in retaining sediment and nutrients (dissolved, total, and particulate nitrogen and phosphorus) from widely available variables (width, vegetation, slope, soil texture, flow pathway, nutrient form). To evaluate the influence of the parent nodes and how the number of states affected the prediction errors, they used a predefined general BN structure, collected 580 published datasets from North America and Europe, and performed classification tree analyses and multiple 10-fold cross-validations of different BNs. These errors ranged from 0.31 (two output states) to 0.66 (five states). The outcome remained unchanged without the least influential nodes (flow pathway, vegetation). Lower errors were achieved when the parent nodes had more than two states. The number of efficacy states influenced most strongly by the prediction error as its lowest and highest states were better predicted than the intermediate states. While the derived BNs could support or replace simple design guidelines, they are limited for more detailed predictions. More representative data on vegetation or additional nodes, such as preferential flow, would probably improve the predictive power [18].

2.3. Monitoring, Modeling, and Management

The contamination of water with nutrients, especially nitrogen and phosphorus originating from various diffuse and point sources, has become a worldwide issue in recent decades. Due to the complexity of the processes involved, watershed models are gaining an increasing role in their analysis. The goal set by the EU Water Framework Directive to reach “good status” for all water bodies requires spatially detailed information on the fate of contaminants. In a study by Jolánkai et al. [19], the watershed nutrient model MONERIS was applied to the Hungarian part of the Danube River Basin. The spatial resolution was 1078 water bodies (mean area of 86 km²), and two subsequent 4 year periods (2009–2012 and 2013–2016) were modeled. Various elements/parameters of the model were adjusted and tested against surface and subsurface water quality measurements taken from all over the country, namely (i) the water balance equations (surface and subsurface runoff), (ii) the nitrogen retention parameters of the subsurface pathways (excluding tile drainage), (iii) the shallow groundwater phosphorus concentrations, and (iv) the surface water retention parameters. The study revealed that (i) digital-filter-based separation of surface and subsurface runoff yielded different values for these components, but this change did not influence nutrient loads significantly; (ii) shallow groundwater phosphorus concentrations in the sandy soils of Hungary differ from those of the MONERIS default values; (iii) a significant change of the phosphorus in-stream retention parameters was needed to approach measured in-stream phosphorus load values. Local emissions and pathways were analyzed and compared with previous model results [19].

Environmental management decisions should be made based on solid scientific evidence, and which relies on monitoring and modeling. In practice, changing economic, societal, and political boundary conditions often interfere with management during large, long, and complex projects. The result may be a sub-optimal development path that may finally diverge from the original intentions and be economically or technically ineffective.

Nevertheless, unforeseen benefits may be created in the end [20]. The Kis-Balaton wetland system is a typical illustration of such a case and has been extensively studied by Honti et al. [20]. Despite tremendous investments and huge efforts put in monitoring and modeling, the sequence of decisions during implementation can hardly be considered optimal. A catchment model and a basic water quality model have been used to coherently review the impacts of management decisions during the 30-year history. Due to the complexity of the system, science mostly excelled in finding explanations for observed changes after the event, instead of predicting the impacts of management measures a priori. In parallel, the political setting and sectoral authorities experienced rearrangements during the system implementation. Despite being expensive as a water quality management investment, originally targeting nutrient removal, the Kis-Balaton wetland system created a huge ecological asset, and thereby became worth the price [20].

3. Conclusions

In this special issue, we are able to present a selection of high-level contributions showing the manifold aspects of monitoring, modeling, and management of water quality. If we look at the chosen subjects we see that four out of the eleven contributions are specifically addressing monitoring aspects and five contributions focus on the interface of modeling and associated monitoring, delivering the scientific basis for water quality management. Only two contributions directly address management aspects in their research focus, indicating that this element of water governance is somehow underrepresented in this special issue. In spite of the small size on the sample, it still points out that the gap between science in its conventional sense and science in an inter- and transdisciplinary understanding is not yet completely closed.

Scientists publishing in a scientific journal still tend to focus on “pure” scientific questions, and use management and policy aspects more for arguing the motivation of their research or as an appendix on what should be considered further, rather than directly including them in their research focus. Therefore additional efforts are needed to bridge the gap between science and policy.

Nevertheless, directly addressing management in the title of a special issue of a scientific journal clearly gives the right sign, and this special issue provides an important overview on a hot topic in water related research. Finally, I would like to thank all the authors for their great contributions and remind you that “he (or she) not busy being born is busy dying” [21].

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References

1. Steffen, W.; Richardson, K.; Rockstrom, J.; Cornell, S.E.; Fetzer, I.; Bennett, E.M.; Sörlin, S. Planetary boundaries: Guiding human development on a changing planet. *Science* **2015**, *347*, 1259855. [[CrossRef](#)] [[PubMed](#)]
2. Zoboli, O.; Clara, M.; Gabriel, O.; Scheffknecht, C.H.; Humer, M.; Briemann, H.; Kulcsar, S.; Trautvetter, H.; Kittlaus, K.; Amann, A.; et al. Occurrence and levels of micropollutants across environmental and engineered compartments in Austria. *J. Environ. Manag.* **2019**, *232*, 636–653. [[CrossRef](#)] [[PubMed](#)]
3. Mayer, R.E.; Reischer, G.H.; Ixenmaier, S.K.; Derox, J.; Blaschke, A.P.; Ebdon, J.E.; Linke, R.; Egle, L.; Ahmed, W.; Blanch, A.R.; et al. Global Distribution of Human-Associated Fecal Genetic Markers in Reference Samples from Six Continents. *Environ. Sci. Technol.* **2018**, *52*, 5076–5084. [[CrossRef](#)] [[PubMed](#)]
4. Limbach, L.K.; Bereiter, R.; Müller, E.; Krebs, R.; Gälli, R.; Stark, W.J. Removal of oxide nanoparticles in a model wastewater treatment plant: Influence of agglomeration and surfactants on clearing efficiency. *Environ. Sci. Technol.* **2008**, *42*, 5828–5833. [[CrossRef](#)] [[PubMed](#)]
5. Rios Mendoza, L.M.; Balcer, M. Microplastics in freshwater environments: A review of quantification and assessment. *Trends Anal. Chem.* **2019**, *113*, 402–408. [[CrossRef](#)]

6. Berendonk, T.U.; Manaia, C.M.; Merlin, C.; Fatta-Kassinos, D.; Cytryn, E.; Walsh, F.; Bürgmann, H.; Sørum, H.; Norström, M.; Pons, M.-N.; et al. Tackling antibiotic resistance: The environmental framework. *Nat. Rev. Microbiol.* **2015**, *13*, 310–317. [[CrossRef](#)] [[PubMed](#)]
7. Zessner, M.; Zoboli, O.; Hepp, G.; Kuderna, M.; Weinberger, C.; Gabriel, O. Shedding Light on Increasing Trends of Phosphorus Concentration in Upper Austrian Rivers. *Water* **2016**, *8*, 404. [[CrossRef](#)]
8. Zessner, M.; Schönhart, M.; Parajka, J.; Trautvetter, H.; Mitter, H.; Kirchner, M.; Hepp, G.; Blaschke, A.P.; Strenn, B.; Schmid, E. A novel integrated modelling framework to assess the impacts of climate and socio-economic drivers on land use and water quality. *Sci. Total Environ.* **2017**, *579*, 1137–1151. [[CrossRef](#)]
9. Schönhart, M.; Trautvetter, H.; Parajka, J.; Blaschke, A.P.; Hepp, G.; Kirchner, M.; Mitter, H.; Schmid, E.; Strenn, B.; Zessner, M. Modelled impacts of policies and climate change on land use and water quality in Austria. *Land Use Policy* **2018**, *76*, 500–514. [[CrossRef](#)]
10. Cao, P.; Zhu, Y.; Zhao, W.; Liu, S.; Gao, H. Chromaticity Measurement Based on the Image Method and Its Application in Water Quality Detection. *Water* **2019**, *11*, 2339. [[CrossRef](#)]
11. Agberien, A.V.; Örmeci, B. Monitoring of Cyanobacteria in Water Using Spectrophotometry and First Derivative of Absorbance. *Water* **2020**, *12*, 124. [[CrossRef](#)]
12. Cao, H.; Guo, Z.; Wang, S.; Cheng, H.; Zhan, C. Intelligent Wide-Area Water Quality Monitoring and Analysis System Exploiting Unmanned Surface Vehicles and Ensemble Learning. *Water* **2020**, *12*, 681. [[CrossRef](#)]
13. Caballero, I.; Ruiz, J.; Navarro, G. Sentinel-2 Satellites Provide Near-Real Time Evaluation of Catastrophic Floods in the West Mediterranean. *Water* **2019**, *11*, 2499. [[CrossRef](#)]
14. Wang, X.; Wei, H.; Chen, N.; He, X.; Tian, Z. An Observational Process Ontology-Based Modeling Approach for Water Quality Monitoring. *Water* **2020**, *12*, 715. [[CrossRef](#)]
15. Medupin, C.; Bark, R.; Owusu, K. Land Cover and Water Quality Patterns in an Urban River: A Case Study of River Medlock, Greater Manchester, UK. *Water* **2020**, *12*, 848. [[CrossRef](#)]
16. Hepp, G.; Zessner, M. Assessing the Impact of Storm Drains at Road Embankments on Diffuse Particulate Phosphorus Emissions in Agricultural Catchments. *Water* **2019**, *11*, 2161. [[CrossRef](#)]
17. Dittmer, U.; Bachmann-Machnik, A.; Launay, M.A. Impact of Combined Sewer Systems on the Quality of Urban Streams: Frequency and Duration of Elevated Micropollutant Concentrations. *Water* **2020**, *12*, 850. [[CrossRef](#)]
18. Gericke, A.; Nguyen, H.H.; Fischer, P.; Kail, J.; Venohr, M. Deriving a Bayesian Network to Assess the Retention Efficacy of Riparian Buffer Zones. *Water* **2020**, *12*, 617. [[CrossRef](#)]
19. Jolánkai, Z.; Kardos, M.K.; Clement, A. Modification of the MONERIS Nutrient Emission Model for a Lowland Country (Hungary) to Support River Basin Management Planning in the Danube River Basin. *Water* **2020**, *12*, 859. [[CrossRef](#)]
20. Honti, M.; Gao, C.; Istvánovics, V.; Clement, A. Lessons Learnt from the Long-Term Management of a Large (Re)constructed Wetland, the Kis-Balaton Protection System (Hungary). *Water* **2020**, *12*, 659. [[CrossRef](#)]
21. Dylan, B. It's Alright, Ma (I'm Only Bleeding). In *The Album Bringing It All Back Home*; Columbia Recording: New York, NY, USA, 1965.