water

Editorial

Decision Support Tools for Water Quality Management

Nigel W. T. Quinn [1,*], Ariel Dinar [2] and Vamsi Sridharan [3]

1 Lawrence Berkeley National Laboratory, 1 Cyclotron Road, MS 64-209, Berkeley, CA 94720, USA
2 School of Public Policy, University of California, Riverside, 900 University Ave., Riverside, CA 92521, USA
3 Tetra Tech, 10306 Eaton Place, Fairfax, VA 22030, USA
* Correspondence: nwquinn@lbl.gov

1. Introduction

The sustainability of inland water resources worldwide is becoming increasingly endangered as climate change contributes to the human-induced problems of water supply scarcity and maldistribution. Environmental problems associated with water quality have been receiving some research attention; however, the litany of natural disasters that have accompanied changes faced by water-reliant ecosystems has created a current-day crisis. Multisectoral stressors imposed on water-related ecosystems exacerbate environmental problems. Environmental challenges associated with agriculture faced by the modern world include aquifer depletion [1–6], land subsidence [7–9], the seasonal drying of river flows [10,11], waterlogging [12–14], salinization of river water and aquifers [15,16], and human health impacts from excessive use of fertilizers and pesticides [17–19] as well as the use of a wide range of household chemicals. These problems have a water quality component that requires a radical re-thinking of resource management policy and new tools to help analysts and regulators craft novel solutions. Likewise, municipal and industrial sectors that rely on a high-quality drinking water supply are cognizant of the challenges associated with curtailing pollution, while minimizing the costs of treatment and pollutant disposal (e.g., References [20–22]). As a consequence, urban areas are increasingly looking to holistic [23] and nature-based pollution-abatement strategies [24,25].

While there is a general consensus among policy, scientific, practice, regulatory and management communities that science-based decision support is necessary to manage and mitigate the deleterious effects of water pollution under climate change (Figure 1), how these decision support tools (DSTs) are designed and implemented for different applications remains an open-ended question. Over the past four decades, with the advent and rapid progress in modeling capacity and computational technology, watershed models have increasingly become effective tools for tackling a wide range of issues regarding water resources and environmental management and supporting regulatory compliance. Statistical and machine learning methods are being used to support and even supplant more traditional simulation models to improve the estimation of temporal dynamics and patterns of variability in pollutant concentrations and loads. With the advancements in data-driven analyses and modeling approaches for water quality, there are also rapid developments in such model-based DSTs for water quality management.

These DSTs are playing central roles, in the following aspects: (i) driving socio-economic decision making by helping multi-sectoral participants make better operational decisions; (ii) informing scientific policy and funding investments and guiding research by revealing data and knowledge gaps; (iii) allowing regulatory agencies to track progress towards achieving water quality goals and facilitating policy guidance; (iv) aiding managers and practitioners to make evidence-based water management decisions; and (v) serving as a conduit to the public, providing a means for leveraging citizen science initiatives (Figure 1).

check for updates

Citation: Quinn, N.W.T.; Dinar, A.; Sridharan, V. Decision Support Tools for Water Quality Management. *Water* **2022**, *14*, 3644. https://doi.org/10.3390/w14223644

Received: 2 November 2022
Accepted: 3 November 2022
Published: 11 November 2022

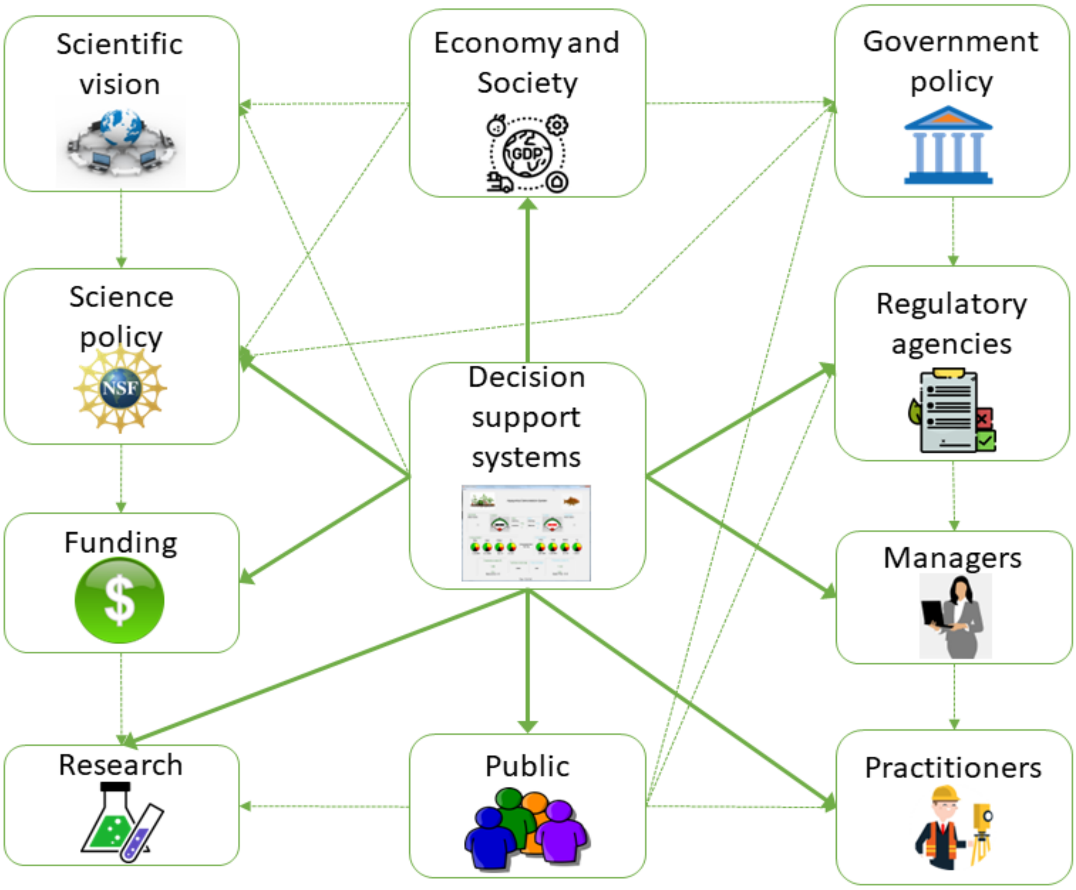

Figure 1. Central role of decision support systems in water quality management. (All icons used in this figure are available freely for public use under creative commons licensing).

The objectives of this Special Issue are to demonstrate the usefulness of decision support tools applied to different types of water quality management issues and to showcase select examples of these issues where contemporary science and technology are used to overcome associated challenges. The aim of this Special Issue within the scientific community is to drive research on emerging tools in water quality management from large-scale, programmatic scopes to small-scale, localized applications. At the same time, it is crucial to highlight the critical role played by stakeholders in supporting programmatic and implementation initiatives, and the need for stakeholder buy-in to ensure the success of water quality management programs. Thus, this Special Issue also highlights how decision support tools can aid in stakeholder participation and engagement.

2. Invitation to Submit to This Special Issue

The call for papers for this Special Issue on "decision tools for water quality management" sought contributions that describe innovative decision support approaches from around the world and across sectors that can be applied by stakeholders, government entities and regulators to reduce environmental pollution, and that can be cost-effective and sustainable.

Submissions from agriculture, municipal and industrial sectors, and environmental ecosystems were encouraged. The selected papers address broad aspects of environmental DSTs, including:

- An overview of water quality sustainability challenges and opportunities.
- Novel or successful techniques to measure and monitor water quantity and quality to achieve sustainable management.
- Sensor and remote sensing technologies that can be integrated with other and more traditional approaches to develop sustainable water quality enhancement strategies.

- Computer-based simulation modeling and other analytical techniques that enhance our understanding of the water quality issues and help formulate solution strategies.
- Benefit–cost analyses that demonstrate economic benefits and costs associated with the development and application of the decision support tool in question.
- Use of various decision support systems for the optimal management of quality aspects of water resources in a regional context and welfare consequences of water quality regulations.

https://www.mdpi.com/journal/water/special_issues/decision_support_tools (accessed on 15 June 2021).

3. Topics Covered by Papers in This Special Issue

This Special Issue consists of eleven papers covering a number of applications and approaches to the provision of decision support to tackle water quality issues. The first paper in the collection provides a policy overview of the importance of Decision Support Tool (DST) development for addressing municipal water quality problems, which is also relevant in other sectors. The applications of DSTs to other sectors is addressed by the other ten papers in this collection. Trends in the use of remote sensing for the development of DSTs used for watershed water quality regulation is explored next, followed by two papers that focus on salinity regulation as it pertains to drainage return flows from irrigated agriculture. The first of these papers is policy-focused and provides an economic perspective on salinity regulation, whereas the second paper describes and assesses the relative performance of two DSTs used in forecasting salt load assimilative capacity in a California river basin. This is followed by three papers that demonstrate various aspects of machine learning and artificial intelligence (AI) in the development of DSTs for water quality regulation at watershed and river basin scales. All three papers deal with forecasting and the interpretation of water quality data using various modeling frameworks. Next, two papers from Israel with an agricultural focus are presented, addressing the blending of saline water supply for optimal crop production and the rehabilitation and preservation of ecosystems, respectively. The next study presents a novel application in the pharmaceutical industry that details the development of a DST to regulate wastewater pollution from the household consumption of personal care products. The DST in this case is a simple ecological impact calculator based on the personal consumption of various products. A final methods paper describes the development of a DST based on tree-ring modeling data that indirectly use the effects of salinity on ecosystem damages. This ordering of papers was chosen in an attempt to provide a coherent thread of topics that starts with the description of various DSTs used for water quality forecasting, management and regulation, including the application of novel modeling approaches. More detailed summaries of each paper follow.

The first paper in this Special Issue—"The Municipal Water Quality Investigations Program: A Retrospective Overview of the Program's First Three Decades" [26] (https://www.mdpi.com/2073-4441/14/21/3426, accessed on 30 October 2022) by Paul Hutton, Sujoy Roy, Stuart Krasner and Leslie Palencia—is a policy paper that presents the history and evolution of the Department of Water Resources' Municipal Water Quality Investigations (MWQI) Program in California, USA. This paper will be of interest to readers involved in developing science-based decision-support capability related to the management of water quality. This paper focuses on regulating water quality in the Sacramento–San Joaquin Delta (Delta), which supplies nearly two-thirds of the population of California with drinking water. Some features of the Program is its ability to provide an early warning of changing conditions in source water quality, as well as data- and knowledge-based support for State Water Project (SWP) operational decision making for a wide variety of urban water users. In their paper, the authors follow Program's formation and its evolution in response to changing regulations and technological advances in water treatment and field monitoring. The paper particularly notes the development of federal drinking water quality regulations, such as the Disinfection By-Products Rule impacted the Program. The MWQI Program is the first drinking water supply program in the United States to conduct a continuous, real-time monitoring of organic carbon, bromide, and anions and to report these data on the internet. Future programs are likely to be guided by factors that trigger changes in treatment plant processes and operations, such as emerging contaminants, changes in land and water management practices, permanent Delta island flooding, sea level rise and climate change.

The second paper—"Can Remote Sensing Fill the United States' Monitoring Gap for Watershed Management?" [27] (https://www.mdpi.com/2073-4441/14/13/1985, accessed on 30 June 2022) by Vamsi Sridharan, Saurav Kumar, and Swetha Kumar—addresses the utility of various remote sensing tools for improving watershed water quality management using regulatory policy vehicles such as total maximum daily loads (TMDLs). An example of remote sensing discussed in the paper is the use of maps with different cost–payoff relationships to help stakeholders plan and incentivize remote-sensing-based water quality monitoring campaigns. One cogent application is the use of cloud cover as a proxy for the likelihood of acquiring remote scenes. The shortest time of travel to population centers was also discussed as a proxy for access to ground-truth imagery for water quality monitoring. Combining spatial indices of population, water demand, ecosystem services, pollution risk, and monitoring coverage deficits in remote-sensing-based in maps can help guide environmental management and the future use of remote sensing products. The authors found that remote sensing applications were most cost-effective for watershed monitoring in the southwestern United States and the central plains regions.

The third paper in this Special Issue—"Developing a Decision Support System for Regional Agricultural Nonpoint Salinity Pollution Management: Application to the San Joaquin River, California" [28] (https://www.mdpi.com/2073-4441/14/15/2384 (accessed on 2 August 2022)) by Ariel Dinar and Nigel Quinn—is one of a number of papers that focus on pressing water quality issues in California. The authors describe a novel stakeholder-centric approach that is being used to manage salinity in the San Joaquin River, which drains some of the most productive agricultural land in the nation and discharges into the Sacramento–San Joaquin River Delta. The authors argue that environmental problems such as salinity, the degradation of receiving waters, and groundwater resource contamination associated with irrigated agriculture require a paradigm shift in resource-management policy and a suite of new decision support tools to create sustainable solutions. The concept of real-time water quality management with a regulatory schema for sharing and allocating cost is described in the paper, as well as the application of this schema to a 20-year time series of flow and salinity data of the San Joaquin River Basin. The paper describes the simulation models and other decision support tools being applied by regulators and stakeholders.

The fourth paper—"Comparison of Deterministic and Statistical Models for Water Quality Compliance Forecasting in the San Joaquin River Basin, California" [29] (https://www.mdpi.com/2073-4441/13/19/2661 (accessed on 30 September 2021)) by Nigel Quinn, Michael Tansey and James Lu—examines two modeling approaches for the forecasting of water flow and quality in the San Joaquin River of California. This San Joaquin River Basin application complements the first paper of this Special Issue, reviewing the models used to implement real-time salinity management (RTSM). Web-based information portals have been developed to share model input data, salt-assimilative-capacity forecasts and provide stakeholder decision support in the River Basin. The paper describes two modeling approaches. The first approach is a statistical model that relies on the relationship between flow and salt concentration at three compliance monitoring sites and the use of these regression relationships for forecasting. The second approach relies on a comprehensive, data-driven computer simulation model of the Basin. The Watershed Analysis Risk Management Framework (WARMF) operates on a daily timestep and estimates daily river salt assimilative capacity along each major river reach. Although the daily regression-based forecasting model provided a marginally better performance, this was partly because the model was updated daily and was able to correct itself, whereas the WARMF model was run weekly and did not have the ability to self-adjust. The physical-based WARMF model has more utility for providing decision support to stakeholders who need to schedule salt loads from contributing watersheds.

The fifth paper—"A Hybrid Model for Water Quality Prediction Based on an Artificial Neural Network, Wavelet Transform, and Long Short-Term Memory" [30] (https://www.mdpi.com/2073-4441/14/4/610 (accessed on 20 February 2022)) by Junhao Wu and Zhaocai Wang—is a machine learning application for water quality assessments in China. This study focuses on water quality prediction in the Jinjiang River using a combination of artificial neural network (ANN), discrete wavelet transform (DWT), and long short-term memory (LSTM) models. Water quality predictions are compared to results from other models, and the results of the study show the superiority of the ANN-WT-LSTM model and suggest its potential as a decision support tool for water quality prediction.

The sixth paper—"Classification and Prediction of Fecal Coliform in Stream Waters Using Decision Trees (DTs) for Upper Green River Watershed, Kentucky, USA" [31] (https://www.mdpi.com/2073-4441/13/19/2790 (accessed on 30 October 2021)) by Abdul Hannan and Jagadeesh Anmala—is another machine leaning application for water quality simulation modeling.

The paper focuses on the classification of stream waters using the parameter of fecal coliform count for instances where there is body contact, such as in recreation, fishing and boating, and domestic utilization. The machine learning techniques involving decision trees can shed light on the structure of input variables, such as climate and land use for stream water quality prediction. The evaluated techniques include the classification and regression tree (CART), iterative dichotomiser (ID3), random forest (RF), and ensemble methods such as bagging and boosting. Input variables are used in the classification of the unknown stream water quality behavior. Of the techniques tested for the classification of fecal coliforms in the upper Green River watershed, Kentucky, USA, DTs with adaptive boosting and bagging were found to be the most accurate.

The seventh paper—"Meeting the Moment: Leveraging Temporal Inequality for Temporal Targeting to Achieve Water-Quality Load-Reduction Goals" [32] (https://www.mdpi.com/2073-4441/14/7/1003 (accessed on 30 March 2022)) by Nicole Opalinski, Daniel Schultz, TamieVeith, Matt Royer, and Heather Preisendanz—focuses on the phenomenon of hydrologic and water quality variation, often expressed as "hot moments" or episodes of unexpectedly high pollutant loading. In their study, the authors developed a Lorenz inequality decision-making framework using Lorenz curves and Gini coefficients to quantify temporal inequality using eight impaired catchments in the Chesapeake Bay watershed. The framework helps to guide the development of site-specific, cost-effective tools for contaminant load reduction and compliance with water quality objectives.

The eighth paper—"Blending Irrigation Water Sources with Different Salinities and the Economic Damage of Salinity: The Case of Israel" [33] (https://www.mdpi.com/2073-4441/14/6/917 (accessed on 20 March 2022)) by Yehuda Slater, Ami Reznik, Israel Finkelshtain, and Iddo Kan—is one of two international papers that focuses on agricultural salinity decision support. Israel has long been recognized as a leader in innovative water conservation and irrigation management technologies. Two strategies for blending water sources with different salinities as an irrigation water supply are compared using a dynamic mathematical programming model that captures this interdependence of hydrology and production economics. The two strategies compare field blending, which enables farmers to assign water with a specific salinity to each crop, with blending at a regional scale. Elevated crop salinity was observed for the regional-scale strategy, and the model results show the largest yield reductions for salt-sensitive crops.

The ninth paper—"Environmental Decision Support Systems as a Service: Demonstration on CE-QUAL-W2 Model" [34] (https://www.mdpi.com/2073-4441/14/6/885 (accessed on 20 March 2022)) by Yoav Bornstein, Ben Dayan, Amir Cahn, Scott Wells, and Mashor Housh—is another contribution from Israel that describes the application of an environmental decision support system (EDSS) for the rehabilitation and preservation of ecosystems. The EDSS is built upon the popular CE-QUAL-W2 model platform with enhancements that are configured to leverage new open-source technologies in software development (i.e., Docker, Kubernetes, and Helm) with cloud computing to significantly reduce implementation costs. For Python programmers familiar with the GitHub repository, new algorithms and executable code can be accessed by the EDSS from GitHub and employed in river basin water quality simulations. A case study is described in the paper from the Yarquon River Authority that combines agriculture and urban stakeholders and a variety of water sources with water quality concerns.

The tenth paper—"Development and Demonstration of an Endocrine-Disrupting Compound Footprint Calculator" [35] (https://www.mdpi.com/2073-4441/14/10/1587 (accessed on 20 May 2022)) by Rachel Taylor, Kathryn Hayden, Marc Gluberman, Laura Garcia, Serap Gorucu, Bryan Swistock, and Heather Preisendanz"—addresses an important topic in municipal water supply decision support. Few wastewater treatment plants were designed to remove chemicals in commonly used personal care products; hence, many of these products and their metabolites persist in plant effluent. Many of these chemicals are potential endocrine-disrupting compounds (EDCs) that cause adverse impacts to aquatic organisms at trace concentrations. The authors developed a public-domain EDC footprint calculator that prompts users to input the number of products they own into categories of health and beauty, laundry, and cleaning and estimate a user's EDC footprint (mass) together with the ranked importance of each product. A case study is presented involving 39 citizen scientists in the northeastern United States, which found the average household EDC footprint to be around 150 g. This decision-making tool can help reduce household footprint impact on future water supply by substituting certain products with greener alternatives.

The eleventh paper in this Special Issue—"Supporting Restoration Decisions through Integration of Tree-Ring and Modeling Data: Reconstructing Flow and Salinity in the San Francisco Estuary over the Past Millennium" [36] (https://www.mdpi.com/2073-4441/13/15/2139 (accessed on 20 August 2022)) by Paul Hutton, David Meko and Sujoy Roy—also focuses on salinity, although this application is further downstream in the Sacramento–San Joaquin River Delta. This paper presents updated reconstructions of watershed runoff into the Estuary from tree-ring data coupled with models that associate rainfall runoff with freshwater flow to the estuary and salinity intrusion. The authors' aim is to better understand the long-term magnitude and seasonality of changes in the Estuary, and thus provide decision support to agency engineers and regulators charged with sustaining adequate freshwater flow to the Estuary and protecting the important anadromous fishery resource. This paper confirms a dramatic decadal-scale hydrologic shift in the watershed from very wet to very dry conditions, which occurred during the late 19th and early 20th centuries, causing an increase in salinity intrusion in the first three decades of the 20th century. Population growth and extensive watershed modification during this period exacerbated this underlying hydrologic shift. Understanding the anthropogenic drivers behind this process is important for setting realistic salinity targets for estuarine restoration.

4. Conclusions

This Special Issue provided a number of modern-day examples of decision support capabilities directed toward improving environmental water quality. The collection of papers in this Special Issue suggest a wide range of issues and regulatory means that can make good use of current state-of-the-art achievements in DSTs and DSSs to improve the policy regulation of deteriorated water quality.

These examples embrace the use of state-of-the-art computer-aided technologies, in particular the use of remote sensing and machine learning, both of which dominate research applications in this field of endeavor. The DSTs derived from the applications of these technologies provide direct and actionable links between scientific research and practice, and this Special Issue highlights how such linkages can be achieved in programmatic, thematic and operational ways. However, despite the excitement generated from these activities, we should not lose sight of the important need to support and carry out basic data collection and data quality assurance activities, as well as the need to strive toward greater dissemination and our ability to share these data. Assessment and interpretation techniques count for nothing if they are based on flawed and inadequate background data. These activities need to march forward in lockstep with advances in decision support capabilities.

Author Contributions: Conceptualization, writing—review and editing, N.W.T.Q., A.D. and V.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The co-guest editors would like to thank all of the authors, reviewers, and editors for their contributions. We are also grateful to the *Water* journal staff for their help and guidance in this Special Issue on "Decision Support Tools for Water Quality Management".

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Feng, W.; Zhong, M.; Lemoine, J.M.; Biancale, R.; Hsu, H.T.; Xia, J. Evaluation of groundwater depletion in North China using the Gravity Recovery and Climate Experiment (GRACE) data and ground-based measurements. *Water Resour. Res.* **2013**, *49*, 2110–2118. [CrossRef]
2. Famiglietti, J. The global groundwater crisis. *Nat. Clim. Chang.* **2014**, *4*, 945–948. [CrossRef]
3. Foster, S.; Custodio, E. Groundwater resources and intensive agriculture in Europe–can regulatory agencies cope with the threat to sustainability? *Water Resour. Manag.* **2019**, *33*, 2139–2151. [CrossRef]
4. Perrone, D.; Jasechko, S. Deeper well drilling an unsustainable stopgap to groundwater depletion. *Nat. Sustain.* **2019**, *2*, 773–782. [CrossRef]
5. Frappart, F. Groundwater storage changes in the major North African transboundary aquifer systems during the GRACE era (2003–2016). *Water* **2020**, *12*, 2669. [CrossRef]
6. Jain, M.; Fishman, R.; Mondal, P.; Galford, G.L.; Bhattarai, N.; Naeem, S.; Balwinder-Singh, U.L.; DeFries, R.S. Groundwater depletion will reduce cropping intensity in India. *Sci. Adv.* **2021**, *7*, eabd2849. [CrossRef]
7. Erban, L.E.; Gorelick, S.M.; Zebker, H.A.; Fendorf, S. Release of arsenic to deep groundwater in the Mekong Delta, Vietnam, linked to pumping-induced land subsidence. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 13751–13756. [CrossRef]
8. Becker, M.; Papa, F.; Karpytchev, M.; Delebecque, C.; Krien, Y.; Khan, J.U.; Ballu, V.; Durand, F.; Le Cozannet, G.; Islam, A.S.; et al. Water level changes, subsidence, and sea level rise in the Ganges–Brahmaputra–Meghna delta. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 1867–1876. [CrossRef]
9. Perkins, S. Often driven by human activity, subsidence is a problem worldwide. *Proc. Natl. Acad. Sci. USA* **2021**, *118*, e2107251118. [CrossRef]
10. Mukherjee, A.; Bhanja, S.N.; Wada, Y. Groundwater depletion causing reduction of baseflow triggering Ganges river summer drying. *Sci. Rep.* **2018**, *8*, 12049. [CrossRef]
11. Olson, K.R.; Lang, J.M. Rio Grande an International Boundary River Is Drying up and in Need of Restoration. *Open J. Soil Sci.* **2021**, *11*, 587–610. [CrossRef]
12. Kang, M.; Jackson, R.B. Salinity of deep groundwater in California: Water quantity, quality, and protection. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 7768–7773. [CrossRef]
13. Tauro, F. River basins on the edge of change. *Science* **2021**, *372*, 680–681. [CrossRef]
14. Shaw, R.E.; Meyer, W.S.; McNeill, A.; Tyerman, S.D. Waterlogging in Australian agricultural landscapes: A review of plant responses and crop models. *Crop Pasture Sci.* **2013**, *64*, 549–562. [CrossRef]
15. Rajmohan, N.; Prathapar, S.A.; Jayaprakash, M.; Nagarajan, R. Vertical distribution of heavy metals in soil profile in a seasonally waterlogging agriculture field in Eastern Ganges Basin. *Environ. Monit. Assess.* **2014**, *186*, 5411–5427. [CrossRef]
16. Singh, A. Soil salinization and waterlogging: A threat to environment and agricultural sustainability. *Ecol. Indic.* **2015**, *57*, 128–130. [CrossRef]
17. Ward, M.H. Too much of a good thing? Nitrate from nitrogen fertilizers and cancer. *Rev. Environ. Health* **2009**, *24*, 357–363. [CrossRef]
18. Carvalho, F.P. Pesticides, environment, and food safety. *Food Energy Secur.* **2017**, *6*, 48–60. [CrossRef]
19. Hurtado-Barroso, S.; Tresserra-Rimbau, A.; Vallverdú-Queralt, A.; Lamuela-Raventós, R.M. Organic food and the impact on human health. *Crit. Rev. Food Sci. Nutr.* **2019**, *59*, 704–714. [CrossRef]
20. Dasgupta, S.; Huq, M.; Wheeler, D.; Zhang, C. Water pollution abatement by Chinese industry: Cost estimates and policy implications. *Appl. Econ.* **2001**, *33*, 547–557. [CrossRef]
21. Zhou, Y.; Khu, S.T.; Xi, B.; Su, J.; Hao, F.; Wu, J.; Huo, S. Status and challenges of water pollution problems in China: Learning from the European experience. *Environ. Earth Sci.* **2014**, *72*, 1243–1254. [CrossRef]
22. Belayutham, S.; Gonzalez, V.A.; Yiu, T.W. A cleaner production-pollution prevention based framework for construction site induced water pollution. *J. Clean. Prod.* **2016**, *135*, 1363–1378. [CrossRef]

23. Wang, M.; Janssen, A.B.; Bazin, J.; Strokal, M.; Ma, L.; Kroeze, C. Accounting for interactions between Sustainable Development Goals is essential for water pollution control in China. *Nat. Commun.* **2022**, *13*, 730. [CrossRef] [PubMed]
24. Ramachandra, T.V.; Va, S.; Asulabha, K.S. Efficacy of rejuvenation of lakes in Bengaluru, India. *Green Chem. Technol. Lett.* **2020**, *6*, 14–26. [CrossRef]
25. Chung, M.G.; Frank, K.A.; Pokhrel, Y.; Dietz, T.; Liu, J. Natural infrastructure in sustaining global urban freshwater ecosystem services. *Nat. Sustain.* **2021**, *4*, 1068–1075. [CrossRef]
26. Hutton, P.; Roy, S.; Kransner, S.; Palencia, L. The Municipal Water Quality Investigations Program: A Retrospective Overview of the Program's First Three Decades. *Water* **2022**, *14*, 3426. [CrossRef]
27. Sridharan, V.K.; Kumar, S.; Kumar, S.M. Can Remote Sensing Fill the United States' Monitoring Gap for Watershed Management? *Water* **2022**, *14*, 1985. [CrossRef]
28. Dinar, A.; Quinn, N.W.T. Developing a Decision Support System for Regional Agricultural Nonpoint Salinity Pollution Management: Application to the San Joaquin River, California. *Water* **2022**, *14*, 2384. [CrossRef]
29. Quinn, N.W.T.; Tansey, M.K.; Lu, J. Comparison of Deterministic and Statistical Models for Water Quality Compliance Forecasting in the San Joaquin River Basin, California. *Water* **2021**, *13*, 2661. [CrossRef]
30. Wu, J.; Wang, Z. A Hybrid Model for Water Quality Prediction Based on an Artificial Neural Network, Wavelet Transform, and Long Short-Term Memory. *Water* **2022**, *14*, 610. [CrossRef]
31. Hannan, A.; Anmala, J. Classification and Prediction of Fecal Coliform in Stream Waters Using Decision Trees (DTs) for Upper Green River Watershed, Kentucky, USA. *Water* **2021**, *13*, 2790. [CrossRef]
32. Opalinski, N.; Schultz, D.; Veith, T.L.; Royer, M.; Preisendanz, H.E. Meeting the Moment: Leveraging Temporal Inequality for Temporal Targeting to Achieve Water-Quality Load-Reduction Goals. *Water* **2022**, *14*, 1003. [CrossRef]
33. Slater, Y.; Reznik, A.; Finkelshtain, I.; Kan, I. Blending Irrigation Water Sources with Different Salinities and the Economic Damage of Salinity: The Case of Israel. *Water* **2022**, *14*, 917. [CrossRef]
34. Bornstein, Y.; Dayan, B.; Cahn, A.; Wells, S.; Housh, M. Environmental Decision Support Systems as a Service: Demonstration on CE-QUAL-W2 Model. *Water* **2022**, *14*, 885. [CrossRef]
35. Taylor, R.; Hayden, K.; Gluberman, M.; Garcia, L.; Gorucu, S.; Swistock, B.; Preisendanz, H. Development and Demonstration of an Endocrine-Disrupting Compound Footprint Calculator. *Water* **2022**, *14*, 1587. [CrossRef]
36. Hutton, P.H.; Meko, D.M.; Roy, S.B. Supporting Restoration Decisions through Integration of Tree-Ring and Modeling Data: Reconstructing Flow and Salinity in the San Francisco Estuary over the Past Millennium. *Water* **2021**, *13*, 2139. [CrossRef]