

Statement of Contribution

This thesis is submitted as a Thesis by Compilation in accordance with

https://policies.anu.edu.au/ppl/document/ANUP_003405 and https://policies.anu.edu.au/ppl/document/ANUP_012815.

I declare that the research presented in this Thesis represents original work that I carried out during my candidature at the Australian National University, except for contributions to multi-author papers incorporated in the Thesis where my contributions are specified in this Statement of Contribution.

Consistent with the author reuse policy, we confirm that the chapter is the original publication, and the publication is not-for-profit for scholarly purposes. The following article is the original publication of 44 pages including eight figures numbered from 1 to 8 and one table (Table 1), further readings and references, named “A Century of Evolution of Modeling for River Basin Planning to the Next Generation of Models, Methods, and Concepts”, by C. Rosello, S. Elsawah, J. Guillaume and A. Jakeman, in 2022, reproduced by permission of Oxford University Press [<https://doi.org/10.1093/acrefore/9780199389414.013.624>]. This article must not be distributed under any kind of Open Access style licences which may affect the Licence with OUP.

Title: A Century of Evolution of Modeling for River Basin Planning to the Next Generation of Models, Methods, and Concepts

Authors: Rosello, C., Elsawah, S., Guillaume, J., & Jakeman, A.

Publication outlet: Oxford Research Encyclopedia of Environmental Science.

<https://oxfordre.com/environmentalscience/view/10.1093/acrefore/9780199389414.001.0001/acrefore-9780199389414-e-624>

Current status of paper: Published

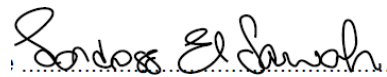
Contribution to paper: Initial literature review and analysis by CR, further evolution thanks to contributions by ES and AJ. Initial draft by CR. All four authors contributed to the manuscript revision, read, and approved the submitted version.

Senior author or collaborating authors endorsement:

Sondoss Elsawah

Joseph Guillaume

Anthony Jakeman







Caroline Rosello



3.3.2024

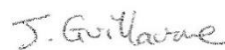
Candidate – Print Name

Signature

Date

Endorsed

Joseph Guillaume



13.2.2024

Primary Supervisor – Print Name

Signature

Date

Robert Dyball



7/3/2024

Delegated Authority – Print Name

Signature

Date

A Century of Evolution of Modeling for River Basin Planning to the Next Generation of Models, Methods, and Concepts **FREE**

Caroline Rosello, Australian National University, Sondoss Elsawah, Australian National University & University of New South Wales, Joseph Guillaume, Australian National University, and Anthony Jakeman, Australian National University

<https://doi.org/10.1093/acrefore/9780199389414.013.624>

Published online: 21 December 2022

Summary

River Basin models to inform planning decisions have continued to evolve, largely based on predominant planning paradigms and progress in the sciences and technology. From the Industrial Revolution to the first quarter of the 21st century, such modeling tools have shifted from supporting water resources development to integrated and adaptive water resources management. To account for the increasing complexity and uncertainty associated with the relevant socioecological systems in which planning should be embedded, river basin models have shifted from a supply development focus during the 19th century to include, by the 2000s–2020s, demand management approaches and all aspects of consumptive and non-consumptive uses, addressing sociocultural and environmental issues. With technological and scientific developments, the modeling has become increasingly quantitative, integrated and interdisciplinary, attempting to capture, more holistically, multiple river basin issues, relevant cross-sectoral policy influences, and disciplinary perspectives. Additionally, in acknowledging the conflicts around ecological degradation and human impacts associated with intensive water resource developments, the modeling has matured to embrace the need for adequate stakeholder engagement processes that support knowledge-sharing and trust-building and facilitate the appreciation of trade-offs across multiple types of impacts and associated uncertainties. River basin models are now evolving to anticipate uncertainty around plausible alternative futures such as climate change and rapid sociotechnical transformations. The associated modeling now embraces the challenge of shifting from predictive to exploratory tools to support learning and reflection and better inform adaptive management and planning. Managing so-called deep uncertainty presents new challenges for river basin modeling associated with imperfect knowledge, integrating sociotechnical scales, regime shifts and human factors, and enabling collaborative modeling, infrastructure support, and management systems.

Keywords: adaptive planning, optimization, participation, River Basin models, scale, scenarios, simulation, systems, uncertainty

Subjects: Management and Planning

Evolution of River Basin Modeling

River Basin (RB) management can be traced back to the first millennium BCE, when water resources were managed predominantly by municipalities or local communities. With the Industrial Revolution in Western countries in the 18th century, water resources became the state's responsibility. Since then, management has evolved from a landscape unit to a catchment/river basin unit to support large-scale water resources development and a more centralized

planning approach (Molle, 2009). Over time, water resource planning in river basins has become increasingly integrated. Integration has transitioned from merely entailing the inclusion of scales for allocating water among users for socioeconomic purposes towards integrating water quality, ecological, and broader social and cultural dimensions. Over the last few decades, RB planning has acknowledged uncertainty in the models *and* modeling: the former is due to the complexity of the system being represented, imperfections in scientific knowledge, and data availability; the latter is due to choices made in the modeling process, including problem framing approaches, assumptions, and techniques used in the process and the ways that actors are chosen and engaged.

Up to the 2010s, these models were used as predictive tools, with scant account taken of uncertainty. More recently, research has focused on identifying the critical uncertainties, especially future climates, and reducing and/or managing them. It has led to river basin models used for exploratory purposes, where the plausible range of drivers influential on river basin outcomes is simulated through the models to evaluate the benefits and downsides of management strategies for a basin system over time (Iwanaga et al., 2020). There is also a trend towards using a robust decision-making framework that evaluates vulnerabilities against multiple plausible future scenarios and identifies trade-offs among different system objectives (Marchau et al., 2019).

Although RB models are largely quantitative tools so as to manage the complexity of a planning problem and support analysis of trade-offs, there are several crucial qualitative steps in the modeling process regarding their design, conceptualization, and implementation (e.g., Badham et al., 2019). These steps must bring the best available knowledge and a wide range of perspectives to the table, not only from experts but also from stakeholders (i.e., actors with interests in the outcomes of a planning exercise). With or without models, RB planning requires collaboration and engagement activities tailored to the needs of the problem and available resources (Giupponi et al., 2006; Jakeman et al., 2016).

A historical perspective on river basin modeling from the Industrial Revolution to the first quarter of the 21st century is provided here. It discusses some of the significant advances in river basin planning and their associated links with progress in the sciences and technology, and identifies future challenges. Six main periods are covered, as captured in the headings of the article sections. The evolution of RB modeling is illustrated in the context of water allocation modeling for the Murray–Darling Basin Plan in Australia. Challenges and prospects for next-generation RB modeling are discussed for the period post-2022.

Pre-1920s, the Industrial Revolution, and the Foundation of the River Basin Unit for State-Led and Centralized Water Resources Development

Following the Industrial Revolution in Western countries, water resources were seen as a disordered domain that needed controlling to support large-scale, socioeconomic development. Water development was described as a “hydraulic mission” for taming and civilizing water systems and societies (Molle, 2009). The RB unit emerged as a physical unit of development in

the 18th century together with River Basin Organizations (RBOs) operationalizing the “hydraulic mission” and supporting a “State-led” and “centralized” water resources planning approach (Huitema & Meijerink, 2014), notably with mega-developments in the Indus basin by the British in the 1880s and the Nile in the late 19th century (Molle, 2009) (Figure 1).

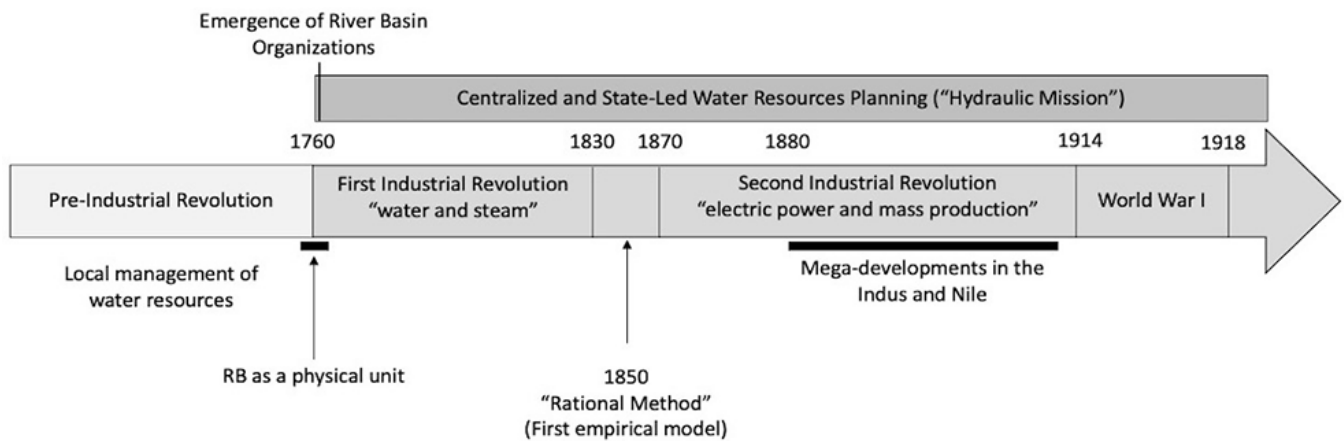


Figure 1. Main developments in the pre-1920s.

Source: Original figure designed by Caroline Rosello

During this era, progress in the water sciences, such as chemistry, sanitation, topography and hydrology, contributed to a more comprehensive description of the hydrological cycle (Figure 2), understanding its components and their connections, and RB model design. Advances included Fick's first law of diffusion for water quality, Darcy's law of flow rate in porous media for groundwater modeling, and the first empirical model for river planning called the “Rational Method,” developed by Mulvaney in 1850 and being at the origin of runoff modeling.

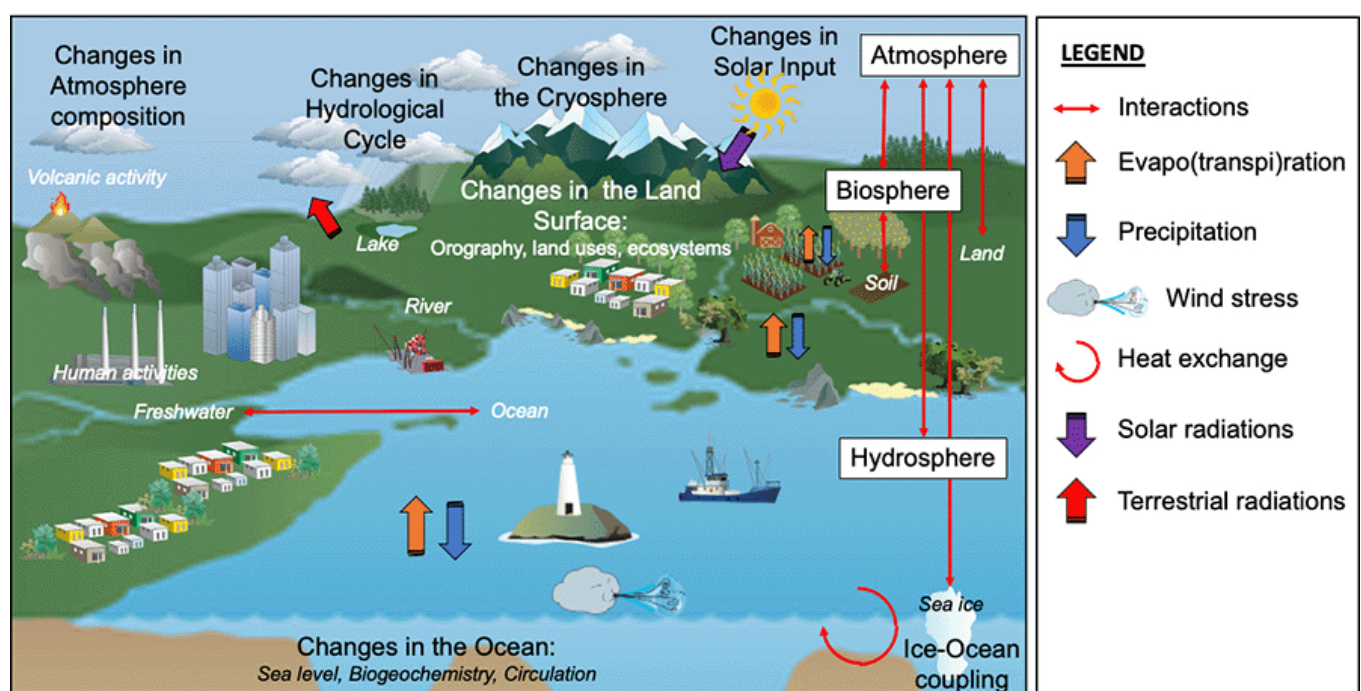


Figure 2. The hydrological cycle.

Source: Loosely adapted from Solomon et al. (2007); designed using Vecta.io with symbols from Integration and Application Network (ian.umces.edu/media-library)

Rational Planning and Intensification of Water Resources Development in the 1920s–1960s

During the first half of the 20th century, different political and socioeconomic factors contributed to the consideration of the RB as a planning and management unit and adoption of rational planning globally. In the United States, to emerge from the Great Depression, the Tennessee Valley Authority (TVA) was the first large-scale and regional development planning project, established by Franklin Roosevelt in 1933, followed by Truman’s exportation of the TVA model to support “democracy” during the Cold War (Molle, 2009) (Figure 3). “River basin accounting,” and cost-benefit analysis in particular, emerged in the 1930s as a decision support tool to support rational planning by identifying economically sound water development projects and formulating economically efficient water allocations, maximizing productivity and the net benefits from water use. In Europe, issues of drainage, water pollution, and hydropower development contributed to institutional changes and the uptake of the RB as a management unit (Molle, 2009).

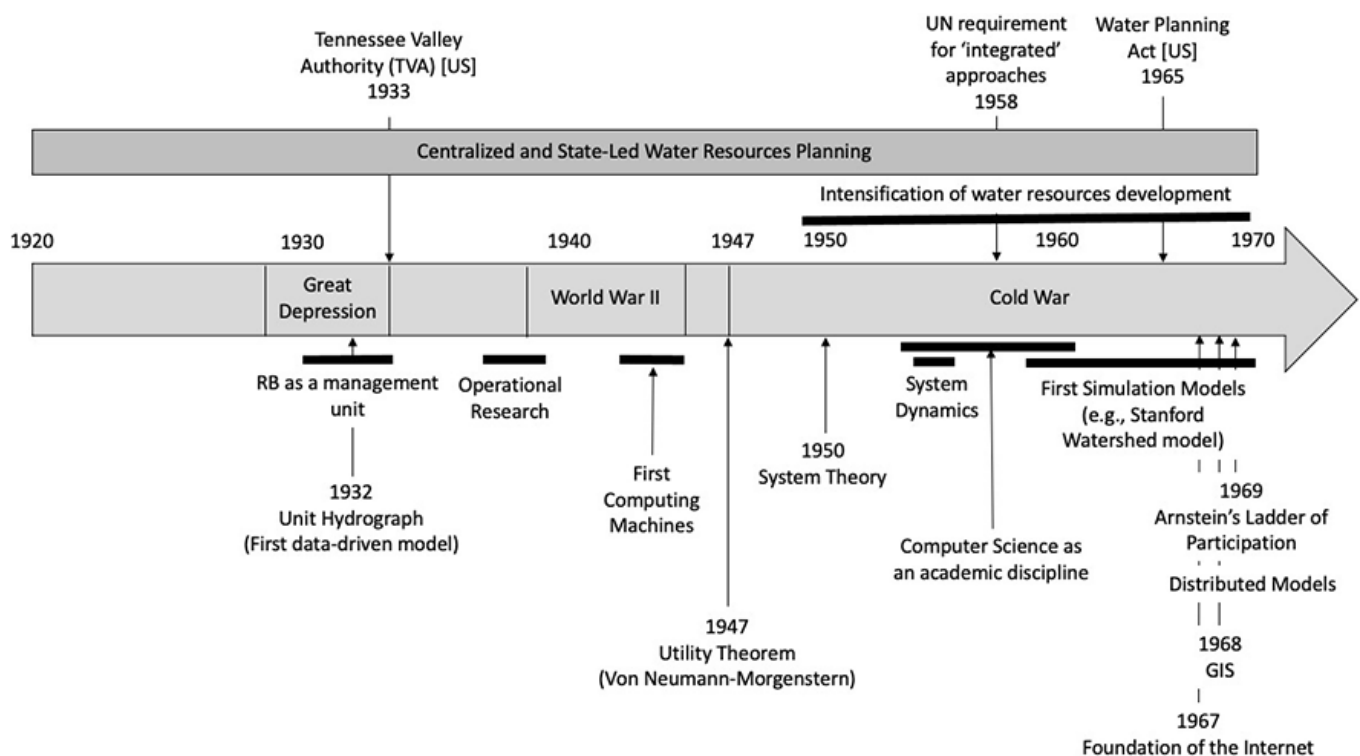


Figure 3. Events in the 1920s–1960s contributing to the emergence of “integrated” RB models.

Source: Original figure designed by Caroline Rosello

Scientific advances in hydrology included development of the unit hydrograph (UH) in 1932 by Sherman, the first data-driven model, and application of optimization methods from Operations Research (OR). By the 1950s, the emergence of System Theory and later System Dynamics, advances in computer sciences, and the UN Department of Economic and Social Affairs report in 1958 contributed to the eventual development of “integrated” simulation models for addressing the complexity of RB planning issues. However, as integrating different technologies was still a challenge, “integration” was understood as embracing broader aspects of the hydrological cycle.

By the late 1960s, water pollution issues were prominent in Western countries. In the United States, the Water Planning Act (1965) instituted a centralized approach and the role of River Basin Organizations to manage water pollution and interstate conflicts and support the implementation of new federal regulations (Huitema & Meijerink, 2014).

Scientific and Technological Advances in the Emergence of Integrated Models

Emergence of Data-Driven vs. Physically Based Water Model Typology

The UH predicts a complete streamflow hydrograph from a unit input of rainfall data. It is an early example of a data-driven model, providing an emerging contrast to physically based models (Todini, 2011; Wheeler et al., 1993).

Data-driven models represent a physical process as an abstract formalism, calibrated using data on system drivers and response. In addition to the UH, examples include statistical models (e.g., linear regression, autoregressive moving average [ARMA]) and machine learning models.

Physically based (also called process-based, mechanistic) models have been influenced by System Theory and are derived from the representation of different features of the hydrological cycle and their relationships. Mathematical formalisms describing cause–effect relationships are less abstract, and many were derived from the physically based equations of fluid mechanics and thermodynamics. With progress in the computer sciences and mathematical programming, simulation models emerged in the 1960s, with the Stanford Watershed model being the first integrated model representing a complete hydrological cycle. Ensuing models differed in their levels of aggregation and spatial scales of resolution, and three main types would be developed: lumped (node–link), semi-distributed, and distributed.

Node–link models are based on the representation of a river system and the definition of its entry and exit points at “nodes” and relationships materialized as a “link.” Semi-distributed models can be seen as an extension of node–link models with the subdivision of a water system into reaches or sub-basins interconnections. Distributed models, based on the definition of grid cells or a mesh, were developed in the 1970s–1980s, utilizing advances in earth system science. Distributed models are more complex than node–link models, with a more refined representation of flow characteristics and water uses. The cells can be linked hydraulically or merely assumed independent, and their outputs are accumulated at a node. However, the level of spatiotemporal disaggregation and model complexity results in increased computational time and data requirements compared to lumped models.

Influence of Operations Research on the Emergence of Simulation Models

OR foundations are rooted in scientific management in the late 1930s and were later applied to military operations during World War II. The OR approach is based on the mathematical formalization of a situation or problem to identify an optimal solution. This identification of optimal decision choices is grounded in decision theory, often on the assumption of rational choices, including use of optimization algorithms of increasing sophistication. Multiple model types have emerged over time, including analog models, simulation models, stochastic models (e.g., Markov chain), and game-theory models (Loucks & Van Beek, 2017). Advances in the computer sciences since the 1950s inspired by biological analogies included methods for optimization using metaheuristics in Evolutionary Algorithms (EAs), as well as artificial neural networks (ANNs).

Simulation Models

In the late 1960s, quantitative simulation models were developed to answer “what-if” questions about a system of interest and its behavior to support experimentation. Methods used to simulate a system for fluids were based typically on continuum methods (i.e., fields and distributions) and aimed to describe rates of change in values for fields and distributions. Discretization techniques were applied to transform continuous (largely ordinary and partial) differential equations into algebraic expressions that could be calculated step-by-step by a computer model (Winsberg, 2010). These simulation models are the origin of scenario-based models developed in the 1970s that consider a system’s performance in response to different water development actions, particularly infrastructure and socioeconomic development (Riley & Averett, 1970).

System Theory and System Dynamics Concepts in the 1950s—Influence on Model Representations of Complex Systems

System Theory and System Dynamics resulted in changes in model representation of physical processes, shifting from a reductionist approach of a phenomenon of interest to a more holistic approach focused on explaining the system behavior in terms of causal relationships and feedback interactions.

The general recognition of System Theory in the 1950s was due to its unifying idea that concepts and tools could be transposed to multiple disciplinary fields. Furthermore, it allows for the formulation and deduction of principles based on the application of validated and generalized logico-mathematical equations to support understanding and knowledge generation (Von Bertalanffy, 1950). In the late 1950s, the development of System Dynamics introduced the principles for system dynamics methodology based on feedback control theory, understanding the decision-making process, and using computer-based technologies to develop simulation models (Forrester, 1961). Later, in the 1990s, this functionalist systems view was expanded to improve the role of mental models in RB model conceptual representation of a system of interest, based on participatory approaches to model design, with a focus on computer models as “managerial laboratories” for experimentation and learning purposes (Lane, 1999).

Stakeholder Involvement in Water Planning

By the end of the 1960s, the impacts of water developments on the natural environment and people, together with increasing opposition to water development projects, especially major dams, led to the consideration of stakeholders in decision making to mitigate conflicts and reduce the costs of water development projects. The role of the social sciences gained momentum in that period, emphasizing the importance of involving stakeholders in planning activities to foster communication between planners and stakeholders, understand needs and preferences, and ultimately induce social change (Bishop, 1970).

However, despite being acknowledged, involving citizens in planning decisions in the late 1960s was still subject to political contention around “empowering” citizens. Arnstein’s (1969) ladder of participation was both a critique and answer to political fear of citizen participation, showing the relationship between different participation levels with different levels of citizen empowerment. The ladder would be influential in developing future participatory frameworks to engage relevant stakeholders in planning and modeling activities.

Realization of Ecological and Human Impacts in the 1970s–1980s and Neoliberal Approaches to Water Resources Planning

At the beginning of the 1970s, growing evidence of the impact of water development on communities and ecological systems was acknowledged by international conferences, including the 1972 UN Conference on the Human Environment in Stockholm (Figure 4).

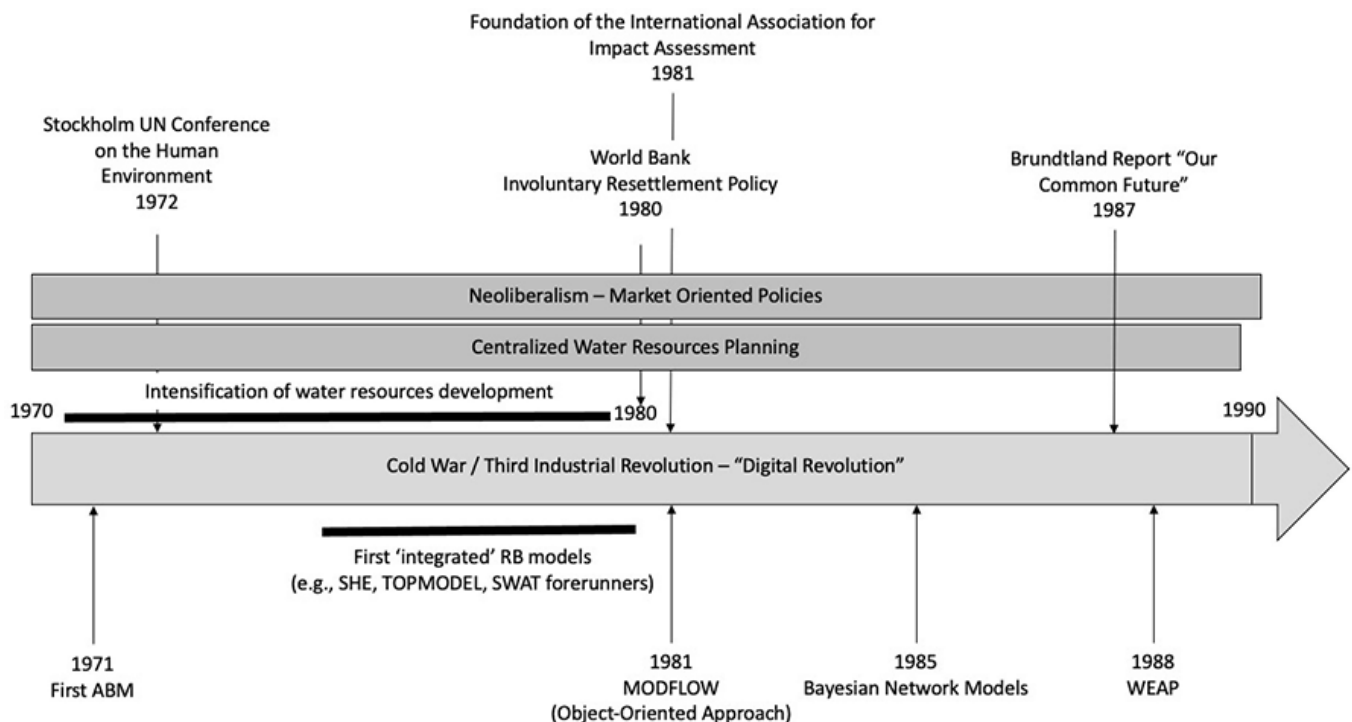


Figure 4. Emergence of integrated RB models in the 1970s–1980s.

Source: Original figure designed by Caroline Rosello

Despite the apparent failure to mitigate conflicts and avoid water quality degradation, the rational planning approach was still viewed as legitimate to support water resources development (Molle, 2009). Additionally, the failure of the state and associated agencies to manage water resources opened the door to neoliberal ideas and the privatization of water resource development projects and associated operation and maintenance. As a result, economic (e.g., water pricing) and market-based approaches became central to informing water allocations.

Compared to previous approaches to water allocation based on economic efficiency, water allocation evolved to include principles of “fairness” and equitable distribution of costs and benefits among water users to ensure the maintenance of water infrastructures and responsible water resource use (Howe et al., 1986). Additionally, with the consideration of human rights and values in decision making, different participatory frameworks, methods and tools to support stakeholder engagement in planning decisions emerged, driven by the social sciences.

Two key developments in RB modeling can be identified in this period: (a) methods to manage variability and uncertainty in complex systems based on advances in the earth system sciences, computer sciences, and mathematics; and (b) microscale (“bottom-up”) approaches wherein patterns and behaviors are inferred from individual/local behaviors (Sabatier, 1986).

Managing Complex Systems Uncertainty and Variability in RB Models

Use of Earth Observation

Advances in the earth system sciences, driven mainly by the national security policy in the United States post World War II and during the Cold War, led to the creation of an enabling environment for oceanography and space research to support strategic control of natural resources (Doel, 2003). Geographical information systems (GIS) and remote sensing technologies contributed markedly to the capability and efficiency in representing different spatial and temporal resolutions of the landscape and biophysical phenomena. Finer scale data enabled increasing RB model complexity to address more issues of concern in RB planning and management, such as how land use and management varies across space, and facilitated calibration of RB model parameters for hydrological processes, such as evapotranspiration or erosion.

In Europe, both SHE (European Hydrological System) (Abbott et al., 1986) and TOPMODEL (TOPography based hydrological MODEL) (Beven et al., 2021) were among the first models in the late 1970s–early 1980s to explicitly use topographic data and consider the relationship between land topography and runoff in a catchment, with SHE driven by the Commission of the European Communities for management purposes, and TOPMODEL by research for ungauged catchments.

In the United States, the U.S. Department of Agriculture’s Agricultural Research Service in the mid-1970s commissioned the CREAMS model (Chemicals, Runoff and Erosion from Agricultural Management Systems), a precursor of SWAT (Soil and Water Assessment Tool), a process-based, nonpoint source, field scale simulation model using topography and remote sensing data to consider land management impacts on water yields, sediments and nutrients. In the 1980s,

several models were developed based on CREAMS to evaluate the impacts of nonpoint source loads on crop yields and groundwater quality, amongst others (Gassman et al., 2007; Krysanova & Arnold, 2008).

In the late 1980s, advances in satellite imagery and remote sensing methods contributed to the generation of digital elevation models and digital analysis in modeling and the use of gridded digital elevation data to predict runoff (Todini, 2011).

Representation of Dynamic and Nonlinear Systems Processes and Behaviors

Two main approaches have been influential in representing dynamic and nonlinear systems processes and behaviors: soft computing methods, and object-oriented approaches (OOA) and software packages.

Soft computing methods (e.g., Artificial Neural Networks [ANN], evolutionary computing, fuzzy computing, swarm intelligence) aim to emulate numerical and process-based models and deal with “imprecision, uncertainty, partial truth, and approximation to achieve practicality, robustness and low solution cost” (Gupta & Kulkarni, 2013). These metaheuristics support a problem-solving approach by using a search algorithm to identify the optimal solutions among a space of possible results (Osman & Laporte, 1996). Their modeling applications included but were not limited to calibration, parameter estimation, and the development of predictive or forecasting models (e.g., flood prediction).

In the 1970s–1980s, OOA became popular. OOA describes objects (e.g., real-world representations), their data (e.g., state variables), behavior (processes), and relationships, and it encourages the application of modules (packages) to maximize the software lifecycle (Capretz, 2003). One example of OOA applied to RB models is MODFLOW, developed by the U.S. Geological Survey (USGS) in 1981 to simulate groundwater flows (McDonald & Harbaugh, 1984). In the 1970s, simulation of groundwater flow using a modular finite-difference flow model was still limited due to computer costs, computational feasibility to run codes to simulate groundwater flow, and incompatibility of research efforts and data formats. In the 1980s these issues were tackled by centralization on a mainframe computer, emphasis on documentation, and development of commercial interactive, character-based programs and training courses to support the use and development of MODFLOW (McDonald & Harbaugh, 1984).

Bayesian Inference and Bayesian Network Approaches to Assess Parameter and/or Output Uncertainty

Bayesian inference developed intensively in the 1970s–1980s to characterize the confidence in predictions of a model. The approach is probabilistic and iterative and considers hierarchically linked hypotheses that could be validated (or not) as more information becomes available (Rubin, 1976). Various applications include model assessment and comparison, parameter estimation and hypothesis testing, sensitivity analysis in simulation models, time-series model assessment, and environmental decision analysis in adaptive management (Ellison, 1996).

Bayesian networks (BNs) also gained momentum as means to describe degrees of beliefs for a system of variables using a combination of graphical models based on node–edge representations and their probabilistic relationships. Probabilities can be obtained from expert opinion, relevant data, or other models (Kelly et al., 2013).

In the 1980s, and more recently, these approaches were used in various contexts related to RB problems, such as evaluating the uncertainty of extrapolated data in flood frequency predictions, freshwater ecosystem investigations, dam reliability assessment, and aquifer management.

Consideration of Stakeholder Preferences and Values

The relationship between socioenvironmental impacts and human actions and policy was increasingly recognized by legislation and adoption of environmental impact assessments (EIAs). These assessments became compulsory for project development in the 1970s in the United States, with the implementation of the National Environmental Policy Act of 1969 (NEPA), and were recommended in the European Economic Community from 1985 and required from 1989. The founding of the International Association for Impact Assessment in 1981 contributed to the international diffusion of EIA, social impact assessment (SIA), and technology assessment. Additionally, the public commitment of the World Bank to include EIAs in their project appraisals in 1986, later reinforced in 1987 by the Brundtland report, was influential in regional donor and lending organizations systematically including EIA and SIA in their project appraisal procedures (Burdge, 1991). This period saw the development of approaches for community participation in planning, but participation was still limited in the late 1980s, as was the representation of human factors in RB models.

In parallel, scenario analysis became more popular to support strategic planning by envisioning different future states of the world. It was seen to improve both quantitative forecasts, often based on extrapolation approaches (e.g., time series), and more qualitative and subjective forecasts, reflective of mental models and preferences. In helping to explore “what-if” questions (Brauers & Weber, 1988), two means of approaching local issues appeared: “top-down” and “bottom-up.”

“Top-down” approaches were based on a holistic idea in which local patterns could be inferred from a system’s global behavior. Economic and market-based approaches to decision choices applied expected utility approaches to rational planning, with an emphasis on ranking decision choices to identify the best solution among a set of options. However, limitations in excluding noneconomic values and marginalizing related stakeholders and interest groups (Schoemaker, 1982) led to more “bottom-up” approaches to decision-making, aiming at inferring global patterns from individual behaviors. Among such approaches, agent-based models (ABM) started to appear in the 1970s–1980s, with the first being Thomas Schelling’s (1971) segregation models, and the first biological ABM containing social features developed by Reynolds (1987). The word “agent” appeared only in the early 1990s, but this nomenclature became increasingly popular.

ABMs were then used to simulate individual or agent autonomous behavior and to seek their influence on emerging patterns, identify flows, market behaviors, organizational risk and design, or diffusion of the adoption of an innovation, among other purposes (Bonabeau, 2002).

Complementing computational representations of behavior, scenario analysis helped to incorporate the human dimension (e.g., values, mental models, decisions) through methods such as INTERAX, using interactive simulations to produce path scenarios, and Battelle's BASICS (Battelle Scenario Inputs to Corporate Strategy) model to produce alternative future views (Huss, 1988).

Finally, scenario analysis expanded RB model utility to consider the consequences of water developments and associated policy actions (e.g., water allocations, water pricing, dam operation rules, multipurpose dam developments) on water systems and livelihoods to support long-term strategic planning (Brauers & Weber, 1988).

Emergence of the IWRM Concept and a Sustainable and Decentralized Approach to Water Resources Management in the 1990s–2000s

The UN Brundtland report in 1987, "Our Common Future," cited the failure of market economies to promote worldwide human welfare and reduce environmental impacts. It also marked the transition from private to cooperative and decentralized management of water resources. Human-induced changes in the environment and the unanticipated response of natural systems to cumulative impacts, especially climate change, led to the emergence of approaches such as resilience-thinking (Perrings, 2006) and socioecological systems (SES) (Berkes & Folke, 1994).

Fundamental to supporting sustainable development was the idea of "integration" of all major aspects of water resource management (Hamilton et al., 2015), including ecological and socioeconomic outcomes, cross-sectoral and uncontrollable influences, and stakeholder perspectives and engagement. This idea led to the emergence of integrated water resources management (IWRM) to operationalize sustainable development by considering water supply development and water demand management to increase water resources availability. IWRM was advocated by the Dublin Principles and incorporated in the 1992 Rio Conference's Agenda 21 and later legitimized by the Global Water Partnership (Lubell & Edelenbos, 2013) (Figure 5).

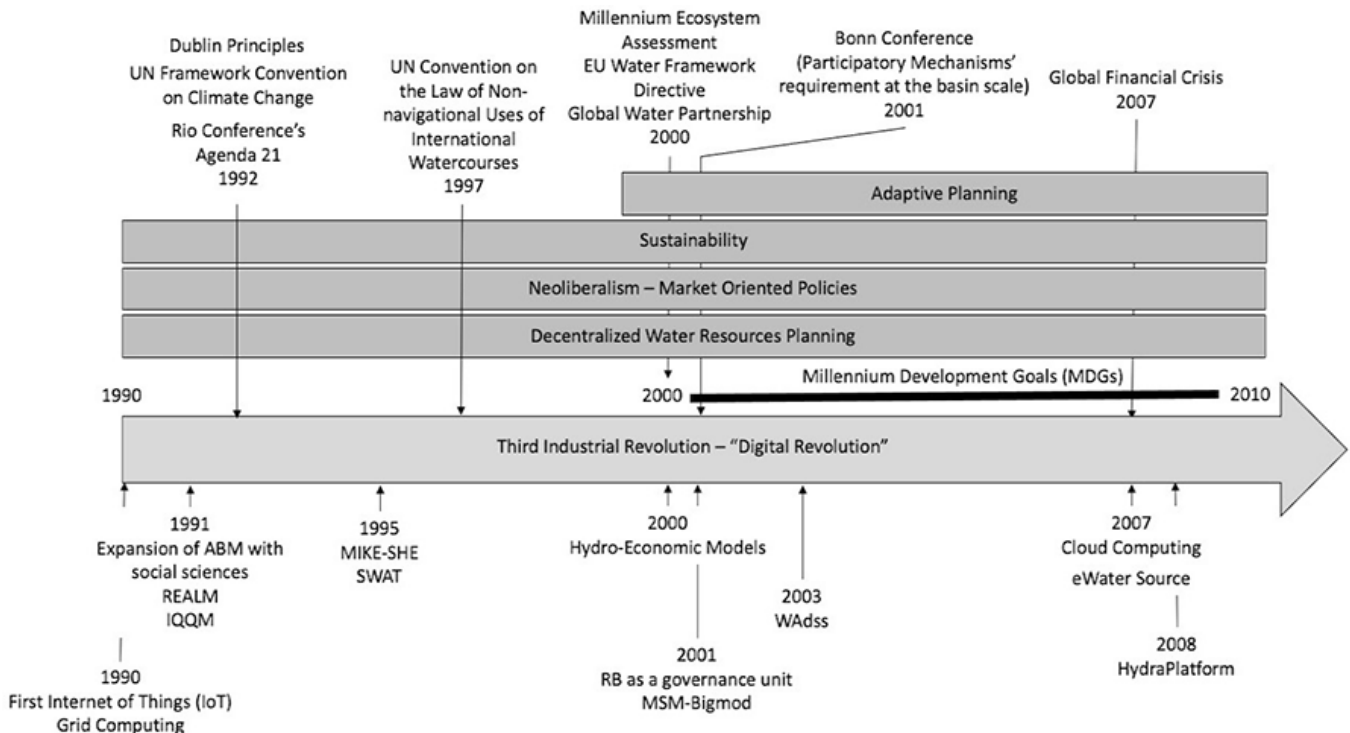


Figure 5. Influence of IWRM on participatory approaches to integrated RB modeling in the 1990s–2000s.

Source: Original figure designed by Caroline Rosello

Another critical evolution in the 1990s–2000s was the consideration of the natural environment as a water user and the need to include ecological water requirements to support sustainable SES. The Millennium Ecosystem Assessment in 2000 mainstreamed the need to maintain sustainable ecosystem services. Challenges for IWRM included traditional means of management based on outdated knowledge and technology and inadequate communication between stakeholders and scientists. Creating networks and public–private partnerships and promoting the adoption of Multi-Objective Decision Support Systems (MODSS) were seen to support the provision of relevant knowledge, inform adaptive planning decisions (Soncini-Sessa et al., 2007), and help achieve multiple societal objectives for a system (Gordon, 1998).

Representing Interdependencies in SES in RB Modeling

Representation of the Connectivity Between Components of the Hydrological Cycle

The consideration of interdependencies between social and ecological systems in the 1990s led to development of integrated model development that brought together multidisciplinary perspectives and modeling approaches about a problem. Bottom–up approaches of SES were represented mainly by ABM and game theory tools, evaluating the performance of a system and policies with explicit consideration of heterogeneity and emergent behavior. Application of ABMs

benefited from development of big data, allowing for the partial validation of such models, and supporting their ability to derive behavioral rules over time using data from diverse sources (Vogel et al., 2015).

Coupled models emerged in response to the demand for interactive and predictive approaches to support adaptive planning (McKinney et al., 1999), combining models reflecting different processes such as climate, soil features, land cover, and crop production. Physical and anthropogenic entities could be attached to supply points (e.g., lakes, reservoirs) and demand points (e.g., irrigation abstractions, domestic and industrial uptakes), and their mutual impacts reflected by indicators for the system performance that are representative of different societal objectives such as water resource scarcity, water quality, agricultural yields, sectoral water productivity, and ecological stress (Giupponi et al., 2006). Examples of coupled hydro-ecological models in the 1990s include SWAT (Arnold & Fohrer, 2005) and MIKE-SHE, an extension of SHE (Refsgaard & Storm, 1995). These two models aim to study the respective influence of hydrological, geochemical, and ecological processes at the catchment level and evaluate current conditions and management alternatives. Their focus was no longer “predictions in gauged and ungauged basins” but “predictions under change.”

The development in the 1990s–2000s of MIKE-SHE was also conditioned by computer capabilities, large investments, and the diffusion of soft packaging solutions to assist in dissemination. Criticisms from the research community regarding overparameterization led, in the 2000s, to the consideration of alternative process formulations and software platforms to combine models, improve river discharge simulations, and consider model uncertainty (Ma et al., 2016).

The SWAT model emerged in the 1990s with the merging of the SWRRB model (Simulator for Water Resources in Rural Basins) with the Routing Output to Outlet (ROTO) model and GRASS (Geographic Resources Analysis Support System) with GIS interface to account for the downstream impact of water management, consider larger areas with many sub-basins, and ease model parameterization for nonhomogeneous basins (Krysanova & Arnold, 2008). Additionally, it dealt with SWRRB computer storage issues associated with a large number of input and output files. During the 1990s–2000s, SWAT evolved to include broader components such as conservation and water management practices and automation of sensitivity, calibration, and uncertainty analysis. The model has since been expanded worldwide and used by various government agencies, especially in the United States and the European Union, to assess climate change impacts on water resources or explore potential future applications for the model (Gassman et al., 2007).

In the 2000s, hydro-economic models gained new traction for improving water allocation assessment, legitimized mainly by the Global Water Partnership (2000) to support IWRM approaches. Their tools include water balance components and water supply infrastructure parameters. Hydrologic and engineering features were integrated using a node-link network in which nodes, representing different social and economic demands, and links were associated with costs or benefits. Another feature of such models was their ability to convert multi-objective problems into single objective ones based on monetary values (Harou et al., 2009). Examples of

hydro-economic models are provided in Harou et al. (2009) and include WEAP (Water Evaluation And Planning system), MIKE-BASIN (Jha & Das Gupta, 2003), and AQUATOOL (Andreu et al., 1996).

Access to Relevant and Timely Information

Essential to ensure model support of planning decisions is access to timely and relevant information. In the 1990s, hardware development (e.g., high-speed networks, supercomputers, clusters of workstations) and middleware (i.e., grid computing) infrastructures enabled large multidisciplinary and collaborative research and the production of real-time information, the management of large quantitative data (big data), and the development of computationally cost-effective modeling tools (Li et al., 2018). For example, grid computing allowed for the connection of supercomputers to personal ones, bringing improved computational efficiency to RB models. Another notable development is the use of surrogate models for calibration, sensitivity analysis, or uncertainty analysis purposes. Their types can be data-driven, projection-based, or physically based models (Razavi et al., 2012).

Considering Multiple Objectives for System Performance

The main changes in terms of planning objectives in the 1990s–2000s were the added consideration of recreational and cultural uses of water, and environmental flow requirements (Banks, 1993), in addition to other water uses (e.g., drinking, industrial, hydropower). In the case of environmental flows, measures evolved from a simplified approach to flow requirements based on the maintenance of low flow levels to the development of more holistic and complex approaches for defining environmental flow allocations. Indicators for flow regime alteration include flow duration curves or indices of hydrological alteration (Arthington, 2012). Further, the need to recognize major upstream/downstream relationships (i.e., countries or states sharing the same river basin system) was mainstreamed by the 1997 UN Convention on the Law of Non-Navigational Uses of International Watercourses to manage conflicts and ensure the joint management of shared water resources in an agreed and equitable manner (Beaumont, 2000).

The formulation of clear objectives in adaptive planning aims to guide the identification of adequate policy measures and their evaluation (Loucks & Van Beek, 2017). Addressing multiple objectives and setting sustainable water allocations requires decision support tools to represent different interdependencies in SES and land and water resources management strategies. Examples of water management strategies include developing or supporting water supply (e.g., groundwater extraction based on wells and boreholes, alternative water supplies such as recycled water or desalination), managing water demand in terms of efficiency of use and water conservation behaviors (e.g., education programs, metering, rainfall harvesting), and dealing with uncertainties associated with climate, land use, and socioeconomic changes (Mirchi et al., 2010).

Methods, such as Integrated Assessment Model (IAM) frameworks (e.g., Letcher et al., 2007), and models (either holistic or compartmental) were developed for flow allocations for different uses, considering flow regime impacts on downstream users (e.g., navigation, fisheries, and ecological systems) and on upstream ones (e.g., inundation impacts and recreational/cultural activities). Furthermore, in regard to in-stream reservoir operation rules, optimization models can be used to ensure water supply performance (reliability and size of deficit), and sustainable aquatic ecosystem flows. Tools developed for this purpose included data-driven models, using statistical and data-mining algorithms, and forecasting/predictive models, integrating a simulation and an optimization model.

An example of an integrated model used in planning globally and dealing with multiple objectives (including environmental flow allocations) is WEAP (Sieber, 2006), which was developed by the Stockholm Environment Institute and financed by the Hydrologic Engineering Center of the U.S. Army Corps of Engineers and various agencies worldwide. It has been chiefly used for water assessments in the United States and various developing countries and aims to consider various water-related issues, including water conservation, water rights and allocations, groundwater simulations, reservoir operations, and project cost-benefit analyses, among others. Other key features of WEAP are its user-friendly interface, interactive user support, expandable data structures, and flexibility for users to customize variables, model equations and reports (Sieber, 2006). Another example is RiverWareTM (Zagona et al., 2001), an object-oriented river basin management model developed by the Center for Advanced Decision Support for Water and Environmental Systems at the University of Colorado in the late 1990s and used by water management agencies and utilities in the United States and other countries. Central to RiverWare design is to allow for model structure flexibility to accommodate changing multiple objectives for operational and planning applications, organizational needs for either optimization or simulation uses, and the tailoring of applications. Additionally, the model allows for transboundary negotiation of water operations and could be used alone or coupled with other models or databases (Zagona, 2016).

Examples of country-specific models include REALM (Resource Allocation Model), a computer simulation package used by government agencies in the Australian states of Victoria, Western Australia, and South Australia to support water supply operation and management planning (Perera et al., 2005); or IQQM (Integrated water Quantity and Quality simulation Model), used by government agencies in New South Wales and Queensland (Australia) for water resources management planning (Simons et al., 1996).

Emerging RB Models in the 1990s–2000s

Table 1 illustrates some RB models that emerged in the 1990s–2000s, influenced by advances in science, technology and planning.

Table 1. Examples of forecasting/predictive RB models, main features and examples of their application. Numbers in brackets are linked to associated references. Selected applications are shown – blank examples of applications do not imply that no applications exist. n.d. = no identified information. For node-link style modeling tools, model setup is based on the configuration and parameterization of nodes and links. However, these models could also be considered as semi-distributed when including reaches and sub-reaches to a main river basin.

Integrated models	Compatible analyses		River basin representation	Planning objectives			
	<i>Coupled models</i>	<i>Source code</i>		<i>Flood protection</i>	<i>Water demands for socioeconomic developments</i>	<i>Water quality</i>	<i>Water flows</i>
WEAP	MODFLOW, MODPATH, QUAL2K, PEST	Delphi, C++	Node-link style modeling		✓	✓	✓
SWAT	MODFLOW, Bayesian network	FORTTRAN	Semi-distributed		✓	✓	✓
HEC-HMS	n.d	JAVA	Semi-distributed	✓	✓	✓	✓
MIKE-SHE	MIKE BASIN, MIKE11	.NET (e.g., C#, Python)	Distributed	✓	✓	✓	✓

MIKE BASIN	Aqua Republica	.NET (e.g., C#, Python)	Distributed	✓	✓	✓	✓
eWater Source	Rainfall- runoff models	.NET (e.g., C#, Python)	Node-link style modeling	✓	✓	✓	✓
Hydrogeosphere (HGS)	MODHMS, FRAC3DVS, OASIS, RZWQM2	FORTTRAN	Distributed		✓	✓	✓
Basin Futures	n.d	FORTTRAN	Semi- distributed		✓	✓	✓
AQUATOOL	n.d	Visual Basic, FORTTRAN, C++	Node-link style modeling		✓	✓	✓

Integrated models	Examples of applications							
	Operation rules	Water allocations	Land use planning	Wetland management	Surface water - groundwater conjunctive uses	Water quality management	Water supply and water demand management (including or not climate change)	Stakeholder engagement, capacity building
WEAP					Dehghanipour et al., 2019		Hakami-Kermani et al., 2020	Escobar et al., 2016
SWAT					Aliyari et al., 2019	Sperotto et al., 2019		
HEC-HMS						Weber et al., 2018		
MIKE-SHE			Singh et al., 1999	Copp et al., 2007.		Zhao et al., 2012		
MIKE BASIN	Leemhuis et al., 2009	Jha & Gupta, 2003					Chew et al., 2014	

eWater Source						Mannik et al., 2012	Carr et al., 2012		
Hydrogeosphere (HGS) [1]						Saleem et al., 2020 [1]			
Basin Futures	Under development; capacity building; preliminary assessment of water resources under climate change scenarios (O’Sullivan et al., 2020; Taylor et al., 2021)								
AQUATOOL	Paredes-Arquiola et al., 2013 [2]					[2]	[2]		
Integrated models	Management interventions								
	Economic evaluation	Wetland	Water allocations and sharing rules	Reservoir operations	Land-use planning	Conjunctive use	Water quality	Water demand	Water supply
WEAP	✓		✓				✓	✓	✓
SWAT					✓	✓	✓	✓	✓
HEC-HMS					✓	✓	✓	✓	✓
MIKE-SHE				✓	✓	✓	✓	✓	✓

MIKE BASIN	✓		✓		✓		✓		✓		✓		✓		✓		✓
eWater Source			✓		✓		✓				✓		✓		✓		✓
Hydrogeosphere (HGS)		✓			✓		✓		✓		✓		✓		✓		✓
Basin Futures	✓		✓				✓								✓		✓
AQUATOOL	✓		✓		✓				✓		✓		✓		✓		✓

Note: Numbers in brackets are linked to associated references. Selected applications are shown—blank examples of applications do not imply that no applications exist. n.d. = no identified information. For node-link style modeling tools, model setup is based on the configuration and parameterization of nodes and links. However, these models could also be considered as semi-distributed when including reaches and subreaches to a main river basin.

Improving Modeling Credibility, Transparency, and Relevance: Stakeholder Engagement in Modeling Activities

Through the 1990s, there became a much greater accent on the modeling process, especially related to information credibility, transparency, integrating diverse sources of knowledge, and relevance to the planning or decision problems at hand. Stakeholder participation in the modeling process was recognized as essential for achieving these, as was the role of social learning.

Social learning is defined as both a process and an outcome. It is an interactive and iterative process where stakeholders (i.e., scientists, policymakers, users) share their perspectives and knowledge about a situation to develop a common framework for understanding and managing water resources in a sustainable way (Pahl-Wostl & Hare, 2004). Three interrelated learning requirements need to be addressed: (a) learning about other frames and views, (b) learning about the dynamics and complex interdependencies among ecological and human systems, and (c) learning about uncertainties (Mostert et al., 2008)

Under the influence of social learning, models were seen as “boundary objects,” representative of specific forms of knowledge and mental models about a problem at stake (Franco, 2013). Two major approaches, which can be applied together, have influenced the implementation of social learning: participatory modeling, and scenario-based approaches.

Participatory Modeling

Participatory modeling is an umbrella approach for building models with stakeholders. It involves multiple methods of engagement, largely discussed by Voinov et al. (2018), and includes a range of activities from designing an integrated model to problem analysis using the model designed (Figure 6) (Hamilton et al., 2015).

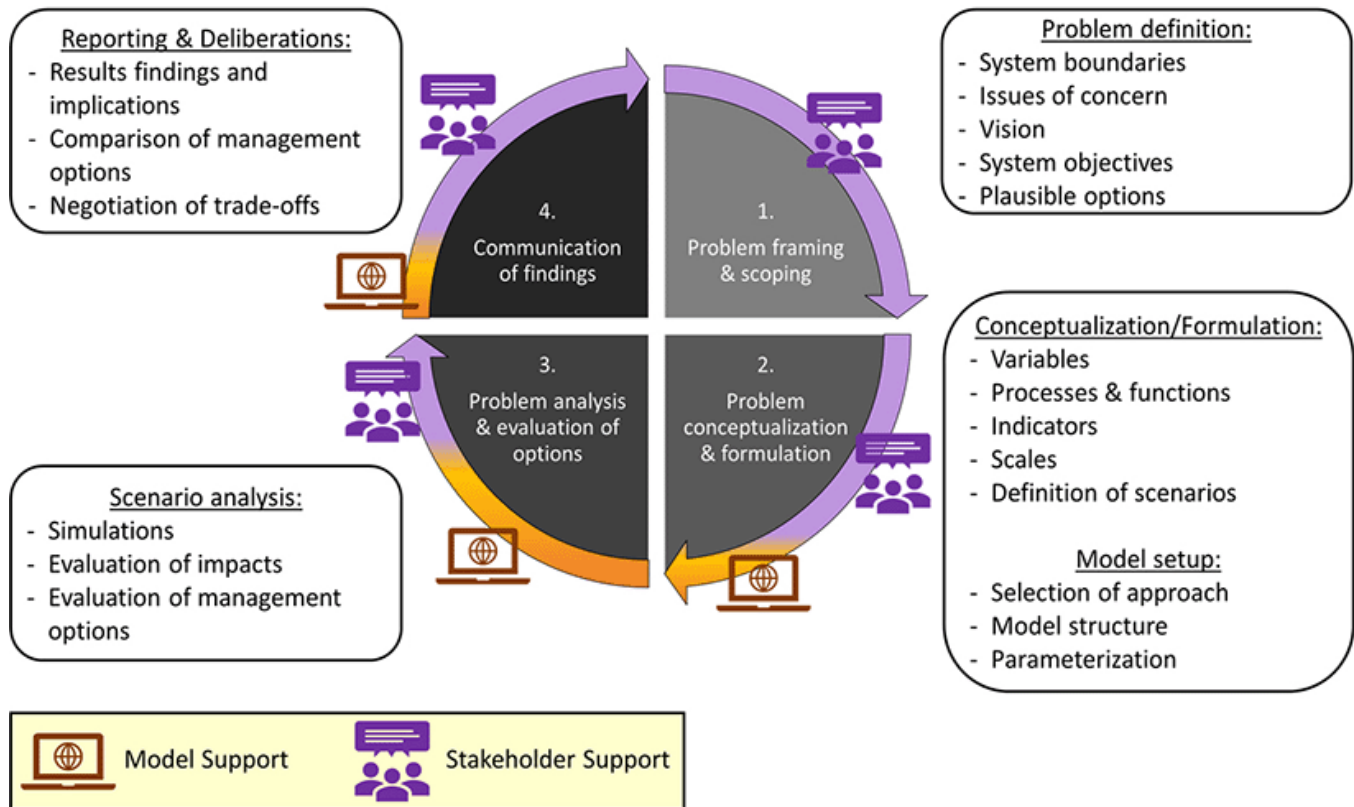


Figure 6. Participatory modeling process, from model design to problem analysis.

Source: Figure adapted from Hamilton et al. (2015)

Examples of models developed with stakeholders include the Water Allocation Decision Support System (WAdss), a hydro-economic model developed for managing water resources in the Gwydir and Namoi catchments in Australia (Letcher, 2005) and, more recently, the Campaspe model, a socioenvironmental model for evaluating sustainable management options in the Lower Campaspe catchment (Iwanaga et al., 2020). In addition, web-based platforms have become increasingly common, such as the HydraPlatform developed to support the collaborative design, use, and user sharing about water resources management models to improve their use and applications for local conditions (Harou et al., 2009).

Scenario-Based Approaches

Scenario-based approaches continued to evolve in the late 1990s–2000s, improving understanding of how to explore a range of possible futures to challenge planning assumptions.

Such an evolution resulted in the emphasis on strategic thinking, rather than strategic planning alone, and a need to consider more flexible and open planning strategies, allowing for creativity, intuition, and learning, to address future uncertainty challenges. Therefore, their purposes evolve from qualitative forecasts to descriptive tools of future conditions to evaluating policy robustness

and adaptiveness under uncertainty. Examples of the impact of scenario development, implications of the choice of spatial and temporal scales, and limitations of scenario-based approaches are reviewed in Dong et al. (2013).

Three main scenario types were used in the 1990s–2000s: strategic, exploratory and anticipatory. Strategic scenarios endeavor to identify inconsistencies in different disciplinary fields when describing complex systems, clarifying the assumptions, patterns, and data from various disciplinary fields. Exploratory scenarios often consider current time as a baseline or benchmark and indicate the change in outcomes from future events relative to current consequences. However, such scenarios are often described as of realistic type and directly represent cause–effect relationships, such as how a climate change scenario may affect system outcomes. Additionally, they might neglect emerging events and their impacts on a system and the effectiveness of actions. Anticipatory scenarios attempt to identify the causes that may lead to a future state. Future objectives and states are the reference points in such approaches, and backward or inverse inferences identify causes rather than consequences. These scenarios can facilitate the consideration of emerging events and the discovery of new options (Börjeson et al., 2006; Liu et al., 2008).

Other typologies used for historical planning studies include future trend-based scenarios that are exploratory and based on extrapolation from past patterns. Future trend-based scenarios can be either projective (i.e., based on forward inferences using trends from past periods) or prospective (i.e., anticipating future changes that significantly vary from past events). Policy-responsive scenarios anticipate ways to achieve desired policy decisions through the construction of scenarios aimed at achieving such policy outcomes. These scenarios can be grounded on expert judgment to define future conditions, or citizen-driven to define assumptions about future events to be included in scenarios (Liu et al., 2008). Scenarios also differed in how they were constructed, notably on whether they were framed, such as by defined axes, or unframed, with a greater freedom of exploration (Maier et al., 2016).

From 2010 to 2021, Managing Uncertainties in Socioecological Systems for Long-Term Adaptive Planning

By the end of the 2000s, IWRM was criticized for its lack of observable benefits, ambiguity in operationalization, and difficulty generalizing as a universal concept (Lubell & Edelenbos, 2013). The river basin unit, as a unit of adaptive management, was also criticized for its lack of fitness to address water issues and management due to natural and humanmade (e.g., infrastructures, water transfers, virtual water) changes, for its fit with administrative boundaries and scales of approach to all water problems, and its decentralized management (Cohen & Davidson, 2011). IWRM limitations to support adaptive management had already been acknowledged by some social scientists in the late 1980s. And in some quarters, its full potential to account for the complexity and interdependencies in human–technology–environment (HTE) systems was not fully realized (Pahl–Wostl et al., 2007).

In the 2010s, the increased scarcity of water resources and questions regarding the future for human societies, especially when considering global issues (e.g., population growth, changes in land use, climate change uncertainty), led to a shift of focus for water resources planning and management to ensure “water security.” The concept was internationally promoted by the Global Water Partnership and the World Economic Forum in 2008 (Cook & Bakker, 2012), and its objectives were later reinforced by the United Nations’ Sustainable Development Goals (SDGs) in 2015, with the consideration of Nexus approaches to set the SDGs (Benson et al., 2015) (Figure 7).

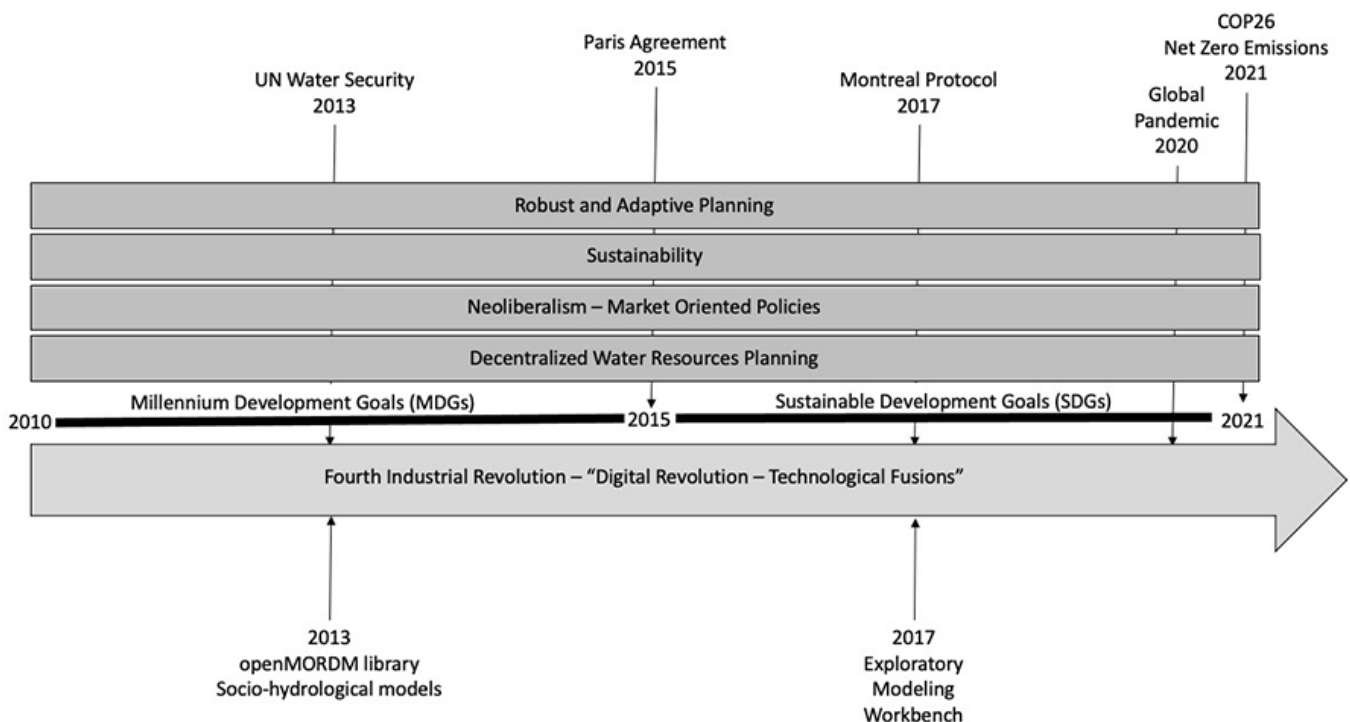


Figure 7. Influence of increased water scarcity and sustainability for model integration from 2010 to 2021.

Source: Original figure designed by Caroline Rosello

In terms of water resources management for decision making, achieving the SDGs requires consideration of the human factors and societal processes in any modeling, recognition of the value of different forms of knowledge, and the consideration of cross-linkages between and within economic, social, and environmental goals. Supporting the implementation of the SDG principles led to reflections around approaches to best develop RB models (Allen et al., 2016).

Furthermore, the emphasis on modeling tools in the 2010s as aids for learning and hypothesis-testing, rather than as forecasting/predictive tools, supported the acknowledgment of irreducible uncertainty and led to the idea of communicating and acknowledging uncertainty in decision making (Walker et al., 2013). Overall, the 2010s era could be described as a new turn in adaptive planning, in terms of considering robust and actionable interventions through the lens of understanding the different aspects of uncertainty affecting SES (Walker et al., 2010) and promoting exploratory modeling approaches to manage future uncertainty (Bankes, 1993).

Approaches to Managing Deep Uncertainty in SES

Deep uncertainty (DU) is a concept that gained impetus through this period. It occurs when experts or parties to a decision do not know, or cannot agree on, the system model boundaries, nonmanageable and exogenous factors to the system model, influential components and associated relationships, and/or performance objectives to measure consequences for the system and/or their relative importance (Lempert et al., 2003). Deep uncertainty also arises from actions taken over time in response to unpredictable evolving situations (Haasnoot et al., 2013).

Approaches to address DU are presented by Marchau et al. (2019). They can be categorized into three groups: resistance-based approaches (i.e., worst scenario planning), resilience-based approaches (i.e., recovery-based approaches to future events), and adaptation-based approaches (i.e., the anticipation of future events). They aim at identifying robust and adaptive solutions, that is, solutions able to cope effectively across various plausible future conditions and implemented according to how the future may unfold (Walker et al., 2010).

Exploratory Modeling and Analysis (EMA) for Robustness Evaluation

EMA is a systematic approach to discover and guide robust decisions and design adaptive policies through exploring and testing simultaneously a wide range of hypotheses and assumptions regarding a system's behavior, rather than predicting it, using a set of plausible models, scenarios, and alternative value systems (Walker et al., 2013). Such an exploratory modeling approach gained momentum from the 2010s, with the need for modeling tools able to address DU and support learning and thinking about "how the world would behave if the various guesses any particular model makes about the various unresolvable uncertainties were correct." It requires the consideration of a large number of computational experiments to explore simultaneously a wide range of uncertainties and the associated dimensional space using dedicated algorithms (Bankes et al., 2013), also enabled in the 2010s by the expansion of cloud computing and increased computational power.

Common methods to analyze extensive computational experiments (as occurs in RB scenario planning) and display a system behavior pattern across the entire uncertainty space make use of statistical or data-mining algorithms, such as the Patient Rule Induction Method (PRIM) or Classification and Regression Trees (CART). Additionally, machine learning and data mining methods of analysis and visualization can be used to cover the uncertainty space and generate a large set of algorithms such as Self Organizing Maps, (t-distributed) Stochastic Nearest Neighbor Embedding, or Support Vector Machines (Bankes et al., 2013). Software tools have been developed to support EMA and include the Exploratory Modeling Workbench (Kwakkel, 2017), the open-source Scenario Discovery Toolkit (Bryant, 2014), and the openMORDM library (Hadka et al., 2015).

Considering Societal Preference Dynamics

Socio-hydrological approaches have gained interest in the hydrological community to analyze human-water systems and associated interdependencies and consider two-way feedback between such systems. They were a key aspect of the International Association of Hydrological Sciences' (IAHS) scientific decade 2013–2022, entitled “Panta Rhei—Everything Flows” and dedicated to research activities on change in hydrology and society. Socio-hydrological approaches aim to interpret emergent patterns and explore the causes and consequences of feedback iteratively through scenario (assumption) evaluation. Compared to other coupled approaches to human-water systems (e.g., hydro-ecological, hydro-economic), socio-hydrology aims at considering dynamic changes within human-water systems associated with the influence of technology-mediated growth and environmental sensitivity (endogenous approach). In contrast, other approaches tend to evaluate the impact of water resources decisions by fixing system boundaries and not considering the impacts of decisions on societal dynamics (exogenous approach) (Pande & Sivapalan, 2017). In 2021, the needs for robust integrated approaches, better considering the reciprocal interactions and current and future implications between human technologies and activities and ecosystems' health and functioning, have been emphasized in the National Academies of Sciences' report about the future of earth systems science (National Academies of Science, Engineering, and Medicine, 2021). According to the report, central to the design and use of such approaches will be the ability to support collaborations and knowledge co-production through fostering a culture for diversity, inclusion, equity, and justice to invite a broad range of actors and perspectives, values, and experiences.

Societal preference changes can also be understood through frameworks that apply many-objectives rather than multi-objective planning approaches. In contrast to multi-objective approaches, which consider fewer objectives without aggregating them under a single monetary unit, many-objective approaches consider simultaneously more objectives and allow for the identification of alternatives that are able to balance many trade-offs simultaneously. Advantages of the approach compared to multi-objective ones are the reduction of decision makers' cognitive myopia, associated with too few or many objectives, and cognitive hysteresis related to the non-consideration of desirable alternatives. Among the frameworks to consider many-objectives approaches is the de Novo framework (Kasprzyk, 2013).

Modeling for Different Data Types and Scales

Bridging Qualitative and Quantitative Knowledge

Bridging different forms of knowledge requires developing mixed qualitative/quantitative models, accessing relevant quantitative and qualitative information, and developing networks and ways to advance social learning and collaboration. In addition to big data, cloud computing and social media have contributed to such advances with the development of web-based platforms to gather qualitative information (thick data) about people's preferences, values, and influential decision factors (Hashemi & Bardsiri, 2012). Cloud computing has also allowed for the development of services to support collaborative modeling and big data management, modeling

tool design, and accessibility to users. However, different challenges are associated with cloud computing and big data, especially security and privacy issues. For example, there are security problems that include communication issues with sharing common resources, computational issues associated with virtualization and data levels, and the need for service level agreements (SLAs) to ensure good practices and compliance of cloud service providers and users (Subramanian & Jeyaraj, 2018).

Modeling Different Scales

In the 1990s–2000s, two approaches were used to define SES problems and evaluate outcomes in response to policy options and/or changes: top-down (scenario-based and goal-driven) or bottom-up (community-based and problem-driven). In the 2010s, these approaches, considered in isolation, were critiqued as too limiting to support sustainability planning, hindering the effective coordination and design of fit-for-purpose policies for different management scales and levels. Instead, mixed qualitative/quantitative approaches (i.e., “middle-out” approaches) were seen to bridge global goals with local problems and improve design of sustainable plans (Zavestoski & Swarnakar, 2017).

The bridging of microscale models to macroscale ones (and vice versa) is slowly developing and is embraced by the concept of system-of-systems approaches (Little et al., 2019). Methods for approaching scales can be divided into data and model scaling approaches. Data scaling methods include inferential (extrapolation, interpolation) and aggregation-based approaches. Model scaling methods are based on modifying parameters, simplifying model structure, deriving response functions or coefficients, and nesting models (Ewert et al., 2011).

Additionally, integrated assessment modelers have used multiple data and model linking methods to approach multiscale problems. A good example is the SEAMLESS-IF model, applied to multiscale agri-environmental problems (Ewert et al., 2011).

However, it would be unrealistic to think that RB models could bridge all scales influential on SES behavior. This holistic objective requires multiscale stakeholder commitment and resources to support multidisciplinary communication and collaboration. It also requires that models be commensurate with available resources and modeling purposes and explicitly consider scale and uncertainty issues (Iwanaga et al., 2021).

Supporting Stakeholder Capacity Building and Collaboration

Stakeholders and decision-makers are central to managing scale and information uncertainty and supporting the design of sustainable plans. Conditional to the provision of relevant information and transforming knowledge into actions is the reduction of communication barriers between scientists and decision-makers by exploiting collaborative modeling approaches and methods in general that enhance information sharing and dissemination (Palmer, 2012).

Collaborative Modeling Approaches to Decision-Making

Collaborative modeling can be regarded as an extension of participatory modeling approaches, involving a high degree of stakeholder participation in building collaborations and taking joint action for mutual benefit or conflict mitigation. Joint action may be facilitated by mechanisms such as partnerships between management organizations or other key stakeholders and the modeling team in the planning and decision-making process (Basco-Carrera et al., 2017).

Assorted modeling tools are available to support collaborative modeling processes. These tools vary from Excel spreadsheet models, agent-based models, Bayesian network models, system dynamics models, and other integrated models, to raster-based visualization models (Kelly et al., 2013; Loucks & Van Beek, 2017). In addition, metamodels have been designed to support decision-making and ease model access and use for nonexperts. Such models allow stakeholders to perform scenario analysis of management alternatives, promote social learning and communication, and support Integrated Catchment Management (Holzkämper et al., 2012).

Cloud-Based Services for Capacity Building and Modeling

Cloud computing became the new platform for data access and management in the 2010s. Compared to grid computing, which was based on a decentralized approach to data management based on data access and storage on local computer devices, cloud computing aims at a centralized approach to data management in data centers, with different services supporting big data management and model design and accessibility, reducing the workload to run applications, and supporting access to information needed only (Kaur & Kaur, 2014). Such services now facilitate collaborative modeling, co-learning, and decision-making processes in river basin management (Sun, 2013). Platforms as a Service (PaaS) has allowed developers to deploy and run open-source applications while minimizing challenges around handling big data (Bahrami & Singhal, 2015). In addition to PaaS, Model as a Service (MaaS) has recently emerged as a new architecture for cloud computing, allowing model simulations and river basin analysis (Chen et al., 2018).

The Use of RB Models for Water Allocation in the Murray Darling Basin

To help the reader contextualize some of the major developments in RB modeling, we use water resource planning in the Australian Murray–Darling Basin (MDB) as an illustrative vignette. Water resource planning in the MDB is an iconic and rich case study for discussing global water issues (Pittock, 2013).

The MDB is the largest river basin in southeastern Australia, covering 1,061,469 km² and encompassing four states and one territory government (Figure 8).

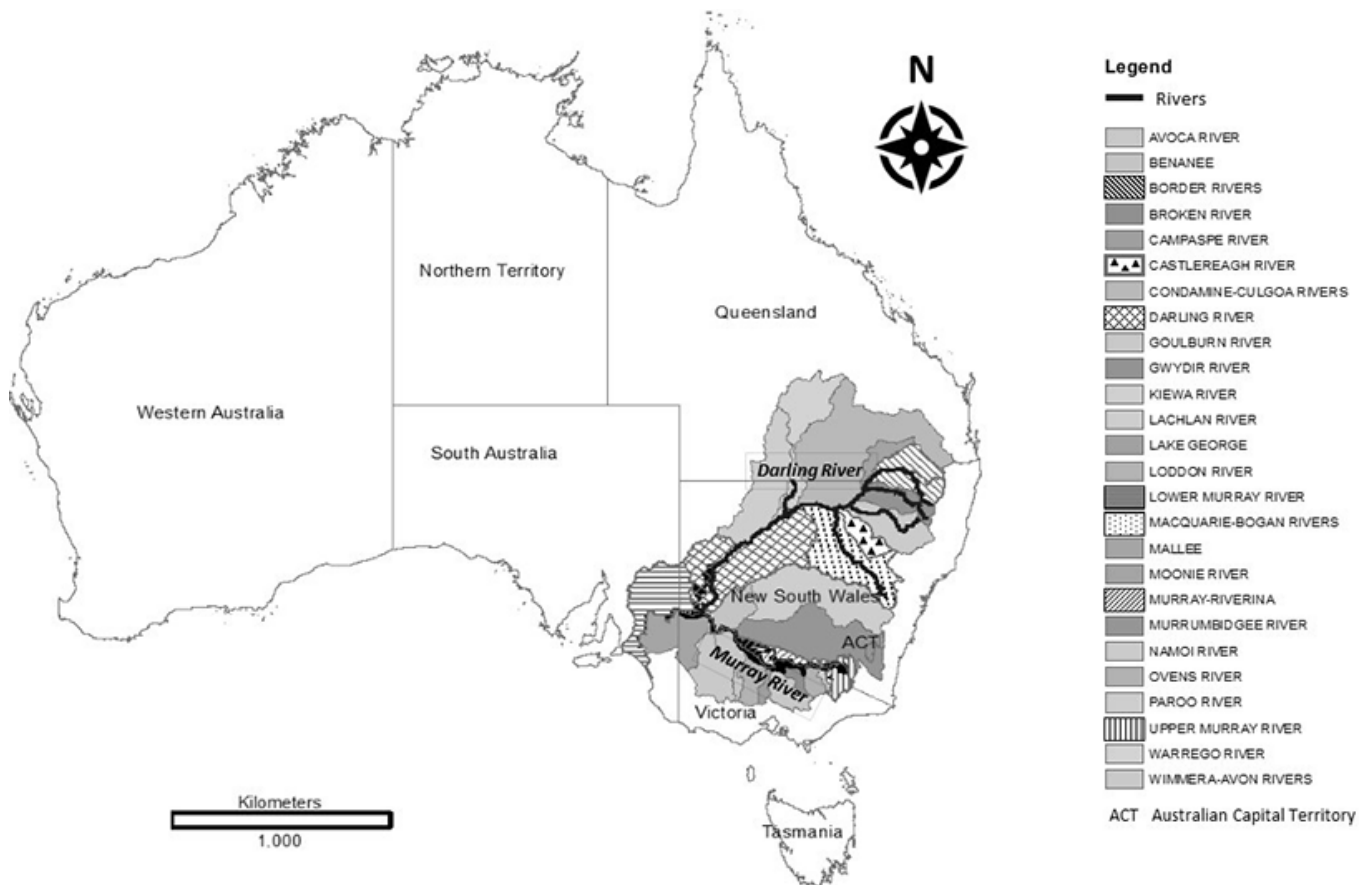


Figure 8. The Murray Darling Basin.

Source: Original figure designed by Caroline Rosello

The basin includes two of the longest Australian rivers: the Murray and Darling Rivers (Figure 8). Thus, climatic conditions vary throughout the basin, from subtropical in the north, to semiarid in the west, and essentially temperate in the south.

Socioeconomically, the basin was home to over two million people in 2014–2015, including 40 Aboriginal nations, and is of critical economic importance in producing 50% of Australia's irrigated agriculture and generating, in 2014–2015, about AU\$19 billion annually in agricultural products. Ecologically, the basin includes about 440,000 km of rivers and 5.7 million ha of wetlands, including 16 RAMSAR sites (Murray–Darling Basin Authority [MDBA], 2016). Water security is an ongoing issue, and each state is responsible for managing water resources.

In regard to integrated models for planning and water allocation, the policy and institutional contexts have been influential on their development and use. The first major policies in the MDB were in the early 20th century with the River Murray Waters Agreement in establishing water shares for New South Wales, South Australia, and Victoria, and in the development of water supply infrastructures to support rural community development (Ross & Connell, 2016). However, nonintegrated modeling approaches were used at that time to address management and operation problems (Malafant & Fordham, 1970).

With the increasing impacts of land-use changes and intensive agricultural practices on surface water and groundwater quality in the 1970s–1980s, more holistic and regional approaches to water management started to gain momentum. Integrated scenario modeling frameworks started to develop to address the challenges of model integration for informing planning and policy decisions based on exploration of alternative futures. Also, with increasing social impacts linked to water developments, these frameworks recognized the need to engage stakeholders through workshops or use stakeholder analysis methodologies (Malafant & Fordham, 1970). The federal and state governments were highly influential in developing integrated models. For example, the development of IQQM in the late 1980s was supported by the Department of Natural Resources (New South Wales, NSW) to investigate water resource management issues (O'Neill et al., 2009).

In the early 1990s, the MDB agreement (1992) extended the scope of different intergovernmental arrangements to include the Darling River and established a “cap” for surface water diversions. There were two objectives regarding the “cap”: improve existing flow regimes to support environmental water requirements, and achieve sustainable consumptive uses. This agreement led to the rapid development of computer simulation models, considering a basin-wide approach, and supporting “cap” setting and compliance (Whittington et al., 2000). To ensure efficient water allocations, these models were expected to integrate surface water and groundwater resources and consider climate change issues in addition to land-use changes and impacts on water resources. For example, IQQM was used throughout the 1990s for Water Allocation Management Planning to generate flow statistics and evaluate abstraction levels for the Border Rivers (Figure 8) (Whittington et al., 2000). The model included modules to assess water quality and groundwater quantity, inform environmental flows, and allow for scenario analysis of up to 100 years of daily flows (Simons et al., 1996).

By the late 2000s, the need for incorporating wider issues in integrated model development and use climaxed. This recognition was influenced mainly by national policies, especially the Australian government's Water Act 2007 and the 2008 Intergovernmental Agreement on the Murray–Darling Basin Reforms; and, in the 2010s, by the development of the 2012 Murray–Darling Basin Plan (Ross & Connell, 2016). This culmination is explained by different requirements to support the Basin Plan, such as each state's responsibility to develop water resources plans (WRP) for its catchments considering a whole-of-system approach to water resources management, to manage various vulnerabilities and uncertainty, optimize environmental outcomes, and support water rights trading, among others (Ross & Connell, 2016).

Since the 2000s, three models have been influential in water resources planning in the MDB: REALM (Victoria and South Australia), IQQM (NSW and Queensland) (Prosser et al., 2012), and, for the Murray Darling Basin Authority (MDBA), MSM-BigMod (Jakeman et al., 2019). However, the misalignment between federal and state management agency modeling tools and the need to modernize such tools to support the responsibilities of water agencies led to the establishment of the eWater Cooperative Research Centre (CRC) in the mid-2000s.

The eWater CRC's role was to support the design of new modeling platforms with a common open access model architecture to underpin catchment modeling. Compared to computer simulation models, the modeling platform consists of compatible and interchangeable modules reflecting

user needs (e.g., “River Manager” to support “cap” roll-out in the MDB for rural water management). It aimed to evaluate climate change effects on hydrology and understand the implications of (future) natural and socioeconomic changes on flow regimes and water supply availability, among other examples (Blackmore & Prosser, 2008).

In 2008, a modeling platform called Source was adopted by the Council of Australian Governments under the National Hydrological Modelling Strategy (NHMS) to support water planning and management. Much of its model conceptualization and representation is based on the previous IQQM model, which is a node-link catchment model. A cross-jurisdictional use case is the model of the Victorian and New South Wales Murray Systems, the Lower Darling River, and the South Australian Murray, known as the Source Murray Model (SMM) (Jakeman et al., 2019).

In 2012, the Basin Plan introduced sustainable diversion limits, setting new limits for water use at the basin level and aiming at replacing the “cap” by 2019. Compared to the “cap,” SDL accounting considers longer historical climate datasets (1895–2009), including the Millennium Drought, water recovered for the environment, permanent water trade adjustment, and different baseline data (MDBA, 2020). In 2018, acknowledging further the need to manage system complexity and uncertainty, the NHMS was updated to consider future objectives for the modeling platform. These objectives were to be: transferable to different Australian regional contexts; relevant and adjustable to new policies, drivers, and knowledge; flexible and interoperable to be able to include new models and other information systems; and to provide ongoing user-support services over the modeling platform life to develop a strong community of practice (eWater, 2022).

In regard to the MDB Plan, issues of cooperation and coordination of actions across governments and water users may reduce its effectiveness to achieve sustainable outcomes. Decentralized and multi-decision-making approaches are still limited and remain primarily associated with land use planning and arrangements to monitor water quality, among other issues (Ross & Connell, 2016). Efforts to include stakeholders are growing and include combining qualitative and quantitative methods as platforms to foster social learning and capacity building.

Examples in the research sphere include Elsayah et al. (2017), who present a methodology for combining semi-qualitative cognitive mapping methods and computational agent-based models, in order to help irrigators elicit and reflect on the assumptions underlying their groundwater use decisions and examine their collective and long-term outcomes. Regarding cloud data and computing services, Wu et al. (2019) used satellite data products from the Australian Geoscience DataCube and online data from Google Earth Engine (GEE) to perform an integrated environmental analysis of the Macquarie–Castlereagh Sub-Basin (Figure 8) to relate land cover/land use to water levels. Their approach illustrates promise for engaging researchers, education and training, and for supporting knowledge production and exchange, reducing computational costs, managing multiple datasets on the same platform, and allowing users to perform global and regional environmental studies.

Next-Generation Challenges and Prospects

Different technical and societal challenges are expected to influence the development and adoption of RB models. From a societal viewpoint, and as illustrated throughout this historical perspective, political visions and decision-maker perceptions of the quality of the information provided by RB models are expected to shape their structure and use. From a technical perspective, three high-level dimensions will need to be conjunctively addressed (Hamilton et al., 2015): key drivers of integration (i.e., stakeholders and experts to involve, problems/issues of interest, governance setting, and applied interventions); focal aspects of a system to be integrated (i.e., human and natural settings, and spatial and temporal scales); and methodological aspects requiring integration (i.e., sources and types of uncertainty, types of methods, models, other tools and data, and disciplines). Elsworth et al. (2020) laid out these technical challenges for socioenvironmental systems more generally. They include holistic management of all critical aspects of uncertainty, better linking human and environmental components, dealing with scales and scaling issues, representing regime shifts and structural change in general, combining quantitative and qualitative methods, and leveraging new data types and sources.

Considering these different levels of integration together with shifts in the human factors require guidance and an iterative process to planning to (a) support knowledge sharing and co-production, (b) overcome data limitations, (c) involve the relevant stakeholders, (d) improve social equity and the consideration of stakeholder voices in the modeling process, and (e) improve uncertainty management in models (Badham et al., 2019; Elsworth et al., 2020). In addition, a significant challenge for model integration will be their level of detail and associated degree of complexity, conditioned by the risk-taking attitude of decision-makers when considering uncertainty in decisions (Madni & Siever, 2014).

Two types of approaches are expected to influence model architecture: data-driven and human-centric approaches. Data-driven approaches are based on the enhanced capability to access real-time and big data with technological progress, improving integrated model performance in terms of simulation and learning, and reducing uncertainty associated with an SES. However, a significant challenge for adopting such models will be managing their complexity and associated distributed architecture to support massive deployments (e.g., technological requirements, knowledge governance, capacity) (Blair et al., 2019).

Compared to data-driven approaches, human-centric ones aim to acknowledge uncertainty associated with open systems, in addition to reducing it when feasible (Madni & Siever, 2014). Such an approach calls for more flexible modeling structures to adjust to user information needs (Reichter & Weber, 2012) and reduce human cognitive overload (Madni & Siever, 2014). Furthermore, it implies a shift in mindset to consider models as iterative and evolving processes and the use of loosely specified process models to adapt dynamically to changes (Reichert & Weber, 2012). In addition, it requires the active participation of the different stakeholder groups to ensure the relevance, credibility, and legitimacy of the information delivered by models (Voinov et al., 2016).

In both cases, challenges to model integration will be associated with model discoverability (i.e., ability to be identified), reusability (i.e., partially or totally reused to improve or serve a new purpose), and interoperability (i.e., ability to communicate between models), as discussed by Belete et al. (2017) in their overview of the model integration process. Also, central to the ability of RB models to serve society and provide relevant insights will be their ability to include human behaviors and actions better, and for the scientific community to demonstrate the value of (new) modeling approaches within the scientific community and to the water resources management community more broadly (Brown et al., 2015).

Overall, critical to the effectiveness of RB models will be their ability to contribute to greater fairness and equity, prosperity and peace, and ecological sustainability (Schwab, 2016). As shown in this historical perspective, since the first Industrial Revolution, the extent to which human and ecological system well-being, values, and right to decency are at the heart of decisions will be conditional on the ability of integrated RB models to inform just and sustainable decisions (Grafton et al., 2022; Menton et al., 2020).

Further Reading

Giupponi, C., Jakeman, A. J., Karssenberg, D., & Hare, M. P. (Eds.). (2006). *Sustainable management of water resources*. Edward Elgar Publishing.

Grafton, R. Q., Fanaian, S., Sacco, G., & Liberman, L. (2022). Bending towards water justice: Pathways for truth, reconciliation, inclusion and transformative actions <<https://doi.org/10.1080/07900627.2021.1952855>>. *International Journal of Water Resources Development*, 38(1), 1–10.

Jakeman, A. J., Barreteau, O., Hunt, R. J., Rinaudo, J.-D., & Ross, A. (Eds.). (2016). *Integrated Groundwater Management: concepts, approaches and challenges* <<http://link.springer.com/book/10.1007%2F978-3-319-23576-9>> (p. 762.). Springer (Open Access).

Jakeman, A. J., Voinov, A. A., Rizzoli, A. E., & Chen, S. H. (Eds.). (2008). *Environmental modeling, software and decision support: State of the art and new perspectives (Developments in integrated environmental assessment, Vol. 3)*. Elsevier.

Loucks, D. P., & Van Beek, E. (2017). *Water resource systems planning and management: An introduction to methods, models, and applications*. Springer.

Marchau, V. A., Walker, W. E., Bloemen, P. J., & Popper, S. W. (Eds.). (2019). *Decision making under deep uncertainty: From theory to practice* <<https://library.oapen.org/handle/20.500.12657/22900>> (p. 405). Springer Nature.

Menton, M., Larrea, C., Latorre, S., Martinez-Alier, J., Peck, M., Temper, L., & Walter, M. (2020). Environmental justice and the SDGs: From synergies to gaps and contradictions <<https://doi.org/10.1007/s11625-020-00789-8>>. *Sustainability Science*, 15(6), 1621–1636.

Novotny, V. (2008). Watershed models <<https://doi.org/10.1016/B978-008045405-4.00240-8>>. In S. E. Jørgensen & B. D. Fath (Eds.), *Encyclopedia of Ecology* (pp. 3748–3759). Academic Press.

Soncini-Sessa, R., Castelletti, A., & Weber, E. (2007). *Integrated and participatory water resources management-theory*. Elsevier.

Sterrett, S. G. (2017). Experimentation on analogue models https://doi.org/10.1007/978-3-319-30526-4_39. In L. Magnani & T. Bertolotti (Eds.), *Springer handbook of model-based science* (pp. 857–878). Springer.

Voinov, A., Kolagani, N., McCall, M. K., Glynn, P. D., Kragt, M. E., Ostermann, F. O., Pierce, S. A., & Ramu, P. (2016). Modeling with stakeholders—Next generation <https://doi.org/10.1016/j.envsoft.2015.11.016>. *Environmental Modelling & Software*, 77, 196–220.

References

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O’Connell, P. E., & Rasmussen, J. (1986). An introduction to the European Hydrological System—Systeme Hydrologique Europeen, “SHE,” 1: History and philosophy of a physically-based, distributed modelling system [https://doi.org/10.1016/0022-1694\(86\)90114-9](https://doi.org/10.1016/0022-1694(86)90114-9). *Journal of Hydrology*, 87(1), 45–59.

Aliyari, F., Bailey, R. T., Tasdighi, A., Dozier, A., Arabi, M., & Zeiler, K. (2019). Coupled SWAT-MODFLOW model for large-scale mixed agro-urban river basins <https://doi.org/10.1016/j.envsoft.2019.02.014>. *Environmental Modelling & Software*, 115, 200–210.

Allen, C., Metternicht, G., & Wiedmann, T. (2016). National pathways to the Sustainable Development Goals (SDGs): A comparative review of scenario modelling tools <https://doi.org/10.1016/j.envsci.2016.09.008>. *Environmental Science & Policy*, 66, 199–207.

Andreu, J., Capilla, J., & Sanchís, E. (1996). AQUATOOL, a generalized decision-support system for water-resources planning and operational management [https://doi.org/10.1016/0022-1694\(95\)02963-X](https://doi.org/10.1016/0022-1694(95)02963-X). *Decision-Support Systems*, 17(3), 269–291.

Arnold, J. G., & Fohrer, N. (2005). SWAT2000: Current capabilities and research opportunities in applied watershed modelling <https://doi.org/10.1002/hyp.5611>. *Hydrological Processes*, 19(3), 563–572.

Arnstein, S. R. (1969). A ladder of citizen participation <https://doi.org/10.1080/01944363.2018.1559388>. *Journal of the American Planning Association*, 85(1), 24–34.

Arthington, A. H. (2012). *Environmental flows: Saving rivers in the third millennium* (Freshwater Ecology Series, Vol. 4). University of California Press.

Badham, J., Elsayah, S., Guillaume, J. H. A., Hamilton, S. H., Hunt, R. J., Jakeman, A. J., Pierce, S. A., Snow, V. O., Babbar-Sebens, M., Fu, B., Gober, P., Hill, M. C., Iwanaga, T., Loucks, D. P., Merritt, W. S., Peckham, S. D., Richmond, A. K., Zare, F., Ames, D., & Bammer, G. (2019). Effective modeling for Integrated Water Resource Management: A guide to contextual practices by phases and steps and future opportunities <https://doi.org/10.1016/j.envsoft.2019.02.013>. *Environmental Modelling & Software*, 116, 40–56.

Bahrami, M., & Singhal, M. (2015). The role of cloud computing architecture in big data. In W. Pedrycz & M. Chen (Eds.), *Information granularity, big data, and computational intelligence* (pp. 275–295). Springer.

Bankes, S. C. (1993). Exploratory modeling for policy analysis <https://doi.org/10.1287/opre.41.3.435>. *Operations Research*, 41(3), 435–449.

- Bankes, S. C., Walker, W. E., & Kwakkel, J. H. (2013). Exploratory modeling and analysis. In S. Gass & M. C. Fu (Eds.), *Encyclopedia of operations research and management science* (3rd ed., pp. 532–537). Springer.
- Basco-Carrera, L., Warren, A., van Beek, E., Jonoski, A., & Giardino, A. (2017). Collaborative modelling or participatory modelling? A framework for water resources management <https://doi.org/10.1016/j.envsoft.2017.01.014>. *Environmental Modelling & Software*, 91, 95–110.
- Beaumont, P. (2000). The 1997 UN Convention on the Law of Non-Navigational Uses of International Watercourses: Its strengths and weaknesses from a water management perspective and the need for new workable guidelines <https://doi.org/10.1080/713672536>. *International Journal of Water Resources Development*, 16(4), 475–495.
- Belete, G. F., Voinov, A., & Laniak, G. F. (2017). An overview of the model integration process: From pre-integration assessment to testing <https://doi.org/10.1016/j.envsoft.2016.10.013>. *Environmental Modelling & Software*, 87, 49–63.
- Benson, D., Gain, A. K., & Rouillard, J. J. (2015). Water governance in a comparative perspective: From IWRM to a “nexus” approach? *Water Alternatives*, 8(1), 756–773.
- Berkes, F., & Folke, C. (1994). *Linking social and ecological systems for resilience and sustainability* http://dlc.dlib.indiana.edu/dlc/bitstream/handle/10535/4352/Berkes-linking_social_and_ecological_systems_for_resilience_and_sustainability.pdf?sequence=1 (Beijer Discussion Paper Series, No. 52). Beijer International Institute of Ecological Economics, The Royal Swedish Academy of Sciences.
- Beven, K. J., Kirkby, M. J., Freer, J. E., & Lamb, R. (2021). A history of TOPMODEL <https://doi.org/10.5194/hess-25-527-2021>. *Hydrology and Earth System Sciences*, 25(2), 527–549.
- Bishop, A. B. (1970, December). *Public participation in water resources planning* (IWR Report 70–7). U.S. Army Corps of Engineers, Institute for Water Resources.
- Blackmore, D., & Prosser, I. (2008). *Report to COAG Water Sub-Group. National hydrologic modelling strategy* <https://ewater.org.au/about-us/nhms/> (p. 38). eWater.
- Blair, G. S., Beven, K., Lamb, R., Bassett, R., Cauwenberghs, K., Hankin, B., Dean, G., Hunter, N., Edwards, L., Nundloll, V., Samreen, F., Simm, W., & Towe, R. (2019). Models of everywhere revisited: A technological perspective <https://doi.org/10.1016/j.envsoft.2019.104521>. *Environmental Modelling & Software*, 122, 104521.
- Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems <https://doi.org/10.1073/pnas.082080899>. *Proceedings of the National Academy of Sciences*, 99(suppl 3), 7280.
- Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., & Finnveden, G. (2006). Scenario types and techniques: Towards a user’s guide <https://doi.org/10.1016/j.futures.2005.12.002>. *Futures*, 38(7), 723–739.
- Brauers, J., & Weber, M. (1988). A new method of scenario analysis for strategic planning <https://doi.org/10.1002/for.3980070104>. *Journal of Forecasting*, 7(1), 31–47.
- Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagana, E. A., Ostfeld, A., Hall, J., Characklis, G. W., Yu, W., & Brekke, L. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management <https://doi.org/10.1002/2015WR017114>. *Water Resources Research*, 51(8), 6110–6124.

- Brundtland, G. (1987). Our common future—Call for action [<https://doi.org/10.1017/S0376892900016805>](https://doi.org/10.1017/S0376892900016805). *Environmental Conservation*, 14(4), 291–294.
- Bryant, B. (2014). *Sdtoolkit: Scenario discovery tools to support robust decision making* [<https://rdr.io/cran/sdtoolkit/>](https://rdr.io/cran/sdtoolkit/) (v2. 33–1) [Package].
- Burdge, R. J. (1991). A brief history and major trends in the field of impact assessment [<https://doi.org/10.1080/07349165.1991.9726070>](https://doi.org/10.1080/07349165.1991.9726070). *Impact Assessment*, 9(4), 93–104.
- Capretz, L. F. (2003). A brief history of the object-oriented approach [<https://doi.org/10.1145/638750.638778>](https://doi.org/10.1145/638750.638778). *ACM SIGSOFT Software Engineering Notes*, 28(2), 6.
- Carr, R., Wong, W.-T., & Immaraj, A. (2012). A pilot study of tradeoffs between flood mitigation and supply security for South-East Queensland using eWater source [<https://search.informit.org/doi/10.3316/informit.908069037437323>](https://search.informit.org/doi/10.3316/informit.908069037437323). In *Hydrology and Water Resources Symposium 2012* (pp. 915–922). Engineers Australia.
- Chen, C., Chen, D., Yan, Y., Zhang, G., Zhou, Q., & Zhou, R. (2018). Integration of numerical model and cloud computing [<https://doi.org/10.1016/j.future.2017.06.007>](https://doi.org/10.1016/j.future.2017.06.007). *Future Generation Computer Systems*, 79, 396–407.
- Chew, C., Zabel, A., Lloyd, G. J., Gunawardana, I., & Monninkhoff, B. (2014). A serious gaming approach for serious stakeholder participation [<https://academicworks.cuny.edu/cc_conf_hic/174>](https://academicworks.cuny.edu/cc_conf_hic/174).
- Cohen, A., & Davidson, S. (2011). The watershed approach: Challenges, antecedents, and the transition from technical tool to governance unit. *Water Alternatives*, 4(1), 1–14.
- Cook, C., & Bakker, K. (2012). Water security: Debating an emerging paradigm [<https://doi.org/10.1016/j.gloenvcha.2011.10.011>](https://doi.org/10.1016/j.gloenvcha.2011.10.011). *Global Environmental Change*, 22(1), 94–102.
- Copp, R., Rowney, C., & Nath, A. (2007). *Development of an integrated surface water-groundwater model for wetland restoration and habitat evaluation in a southwest Florida basin using MIKE SHE Part III: Application of the regional scale model* [<https://doi.org/10.1061/40927\(243\)632>](https://doi.org/10.1061/40927(243)632). Paper presented at the World Environmental and Water Resources Congress 2007.
- Dehghanipour, A. H., Zahabiyoun, B., Schoups, G., & Babazadeh, H. (2019). A WEAP-MODFLOW surface water-groundwater model for the irrigated Miyandoab plain, Urmia lake basin, Iran: Multi-objective calibration and quantification of historical drought impacts [<https://doi.org/10.1016/j.agwat.2019.105704>](https://doi.org/10.1016/j.agwat.2019.105704). *Agricultural Water Management*, 223, 105704.
- Doel, R. E. (2003). Constituting the postwar earth sciences: The military's influence on the environmental sciences in the USA after [<https://doi.org/10.1177/0306312703335002>](https://doi.org/10.1177/0306312703335002). *Social Studies of Science*, 33(5), 635–666.
- Dong, C., Schoups, G., & van de Giesen, N. (2013). Scenario development for water resource planning and management: A review [<https://doi.org/10.1016/j.techfore.2012.09.015>](https://doi.org/10.1016/j.techfore.2012.09.015). *Scenario Method: Current Developments in Theory and Practice*, 80(4), 749–761.
- Ellison, A. M. (1996). An introduction to Bayesian inference for ecological research and environmental decision-making [<https://doi.org/10.2307/2269588>](https://doi.org/10.2307/2269588). *Ecological Applications*, 6(4), 1036–1046.

- Elsawah, S., Hamilton, S. H., Jakeman, A. J., Rothman, D., Schweizer, V., Trutnevyte, E., Carlsen, H., Drakes, C., Frame, B., Fu, B., Guivarch, C., Haasnoot, M., Kemp-Benedict, E., Kok, K., Kosow, H., Ryan, M., & van Delden, H. (2020). Scenario processes for socio-environmental systems analysis of futures: A review of recent efforts and a salient research agenda for supporting decision making <<https://doi.org/10.1016/j.scitotenv.2020.138393>>. *Science of the Total Environment*, 729, 138393.
- Elsawah, S., Pierce, S. A., Hamilton, S. H., van Delden, H., Haase, D., Elmahdi, A., & Jakeman, A. J. (2017). An overview of the system dynamics process for integrated modelling of socio-ecological systems: Lessons on good modelling practice from five case studies <<https://doi.org/10.1016/j.envsoft.2017.03.001>>. *Environmental Modelling & Software*, 93, 127–145.
- Escobar, M., Carvajal, B.-S., Rubiano, J., Mulligan, M., & Candelo, C. (2016). Building hydroliteracy among stakeholders for effective water benefit sharing in the Andes <<https://doi.org/10.1080/02508060.2016.1174546>>. *Water International*, 41(5), 698–715.
- eWater. (2022). *National Hydrological Modelling Strategy (NHMS), 2018* <<https://ewater.org.au/about-us/nhms/>> [Updated draft].
- Ewert, F., van Ittersum, M. K., Heckeley, T., Therond, O., Bezlepikina, I., & Andersen, E. (2011). Scale changes and model linking methods for integrated assessment of agri-environmental systems <<https://doi.org/10.1016/j.agee.2011.05.016>>. *Scaling Methods in Integrated Assessment of Agricultural Systems*, 142(1), 6–17.
- Forrester, J. W. (1961). *Industrial dynamics*. MIT Press.
- Franco, A. L. (2013). Rethinking Soft OR interventions: Models as boundary objects <<https://doi.org/10.1016/j.ejor.2013.06.033>>. *European Journal of Operational Research*, 231(3), 720–733.
- Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The soil and water assessment tool: Historical development, applications, and future research directions. *Transactions of the ASABE*, 50(4), 1211–1250.
- Giupponi, C., Jakeman, A. J., Karssenberg, D., & Hare, M. P. (Eds.). (2006). *Sustainable management of water resources*. Edward Elgar Publishing.
- Global Water Partnership. (2000). *Towards water security: A framework for action*.
- Gordon, M. (1998). *Formulating objectives for management on an ecosystem scale* <<http://hdl.handle.net/10214/15831>>. Ontario Ministry of the Environment.
- Grafton, R. Q., Fanaian, S., Sacco, G., & Liberman, L. (2022). Bending towards water justice: Pathways for truth, reconciliation, inclusion and transformative actions <<https://doi.org/10.1080/07900627.2021.1952855>>. *International Journal of Water Resources Development*, 38(1), 1–10.
- Gupta, P., & Kulkarni, N. (2013). An introduction of soft computing approach over hard computing. *International Journal of Latest Trends in Engineering and Technology (IJLTET)*, 3(1), 254–258.
- Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world <<https://doi.org/10.1016/j.gloenvcha.2012.12.006>>. *Global Environmental Change*, 23(2), 485–498.

- Hadka, D., Herman, J., Reed, P., & Keller, K. (2015). An open source framework for many-objective robust decision making [_<https://doi.org/10.1016/j.envsoft.2015.07.014>_](https://doi.org/10.1016/j.envsoft.2015.07.014). *Environmental Modelling & Software*, 74, 114–129.
- Hakami-Kermani, A., Babazadeh, H., Porhemmat, J., & Sarai-Tabrizi, M. (2020). An uncertainty assessment of reservoir system performance indices under the climate change effect [_<https://doi.org/10.1016/j.asej.2020.03.015>_](https://doi.org/10.1016/j.asej.2020.03.015). *Ain Shams Engineering Journal*, 11(4), 889–904.
- Hamilton, S. H., ElSawah, S., Guillaume, J. H. A., Jakeman, A. J., & Pierce, S. A. (2015). Integrated assessment and modelling: Overview and synthesis of salient dimensions [_<https://doi.org/10.1016/j.envsoft.2014.12.005>_](https://doi.org/10.1016/j.envsoft.2014.12.005). *Environmental Modelling & Software*, 64, 215–229.
- Harou, J. J., Pulido-Velazquez, M., Rosenberg, D. E., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2009). Hydro-economic models: Concepts, design, applications, and future prospects [_<https://doi.org/10.1016/j.jhydrol.2009.06.037>_](https://doi.org/10.1016/j.jhydrol.2009.06.037). *Journal of Hydrology*, 375(3), 627–643.
- Hashemi, S. M., & Bardsiri, A. K. (2012). Cloud computing vs. grid computing. *ARPN Journal of Systems and Software*, 2(5), 188–194.
- Holzämper, A., Kumar, V., Surridge, B. W. J., Paetzold, A., & Lerner, D. N. (2012). Bringing diverse knowledge sources together—A meta-model for supporting integrated catchment management [_<https://doi.org/10.1016/j.jenvman.2011.10.016>_](https://doi.org/10.1016/j.jenvman.2011.10.016). *Journal of Environmental Management*, 96(1), 116–127.
- Howe, C. W., Schurmeier, D. R., & Shaw, W. D., Jr. (1986). Innovative approaches to water allocation: The potential for water markets [_<https://doi.org/10.1029/WR022i004p00439>_](https://doi.org/10.1029/WR022i004p00439). *Water Resources Research*, 22(4), 439–445.
- Huitema, D., & Meijerink, S. (2014). The politics of river basin organisations: Institutional design choices, coalitions and consequences [_<https://www.elgaronline.com/view/edcoll/9781782549215/9781782549215.00006.xml>_](https://www.elgaronline.com/view/edcoll/9781782549215/9781782549215.00006.xml). In D. Huitema & S. Meijerink (Eds.), *The politics of river basin organisations* (pp. 1–37). Edward Elgar Publishing.
- Huss, W. R. (1988). A move toward scenario analysis [_<https://doi.org/10.1016/0169-2070\(88\)90105-7>_](https://doi.org/10.1016/0169-2070(88)90105-7). *International Journal of Forecasting*, 4(3), 377–388.
- Iwanaga, T., Partington, D., Ticehurst, J., Croke, B. F. W., & Jakeman, A. J. (2020). A socio-environmental model for exploring sustainable water management futures: Participatory and collaborative modelling in the Lower Campaspe catchment [_<https://doi.org/10.1016/j.ejrh.2020.100669>_](https://doi.org/10.1016/j.ejrh.2020.100669). *Journal of Hydrology: Regional Studies*, 28, 100669.
- Iwanaga, T., Wang, H.-H., Hamilton, S. H., Grimm, V., Koralewski, T. E., Salado, A., ElSawah, S., Razavi, S., Yang, J., Glynn, P., Badham, J., Voinov, A., Chen, M., Grant, W. E., Peterson, T. R., Frank, K., Shenk, G., Barton, C. M., Jakeman, A. J., & Little, J. C. (2021). Socio-technical scales in socio-environmental modeling: Managing a system-of-systems modeling approach [_<https://doi.org/10.1016/j.envsoft.2020.104885>_](https://doi.org/10.1016/j.envsoft.2020.104885). *Environmental Modelling & Software*, 135, 104885.
- Jakeman, T., Croke, B., & Iwanaga, T. (2019). *Independent review of the source model of the Murray and Lower Darling Rivers (SMM)* [_<https://www.mdba.gov.au/sites/default/files/pubs/Independent%20review%20of%20Source%20Murray%20Model%20%28SMM%29%20report_1.pdf>_](https://www.mdba.gov.au/sites/default/files/pubs/Independent%20review%20of%20Source%20Murray%20Model%20%28SMM%29%20report_1.pdf).
- Jha, M. K., & Gupta, A. D. (2003). Application of Mike Basin for water management strategies in a watershed [_<https://doi.org/10.1080/02508060308691662>_](https://doi.org/10.1080/02508060308691662). *Water International*, 28(1), 27–35.

- Kasprzyk, J. R. (2013). *Many objective water resources planning and management given deep uncertainties, population pressures, and environmental change* <https://etda.libraries.psu.edu/files/final_submissions/8222> [Doctoral dissertation], Pennsylvania State University, United States.
- Kaur, R., & Kaur, A. (2014). A review paper on evolution of cloud computing, its approaches and comparison with grid computing. *International Journal of Computer Science and Information Technologies*, 5(5), 6060–6063.
- Kelly (Letcher), R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., Henriksen, H. J., Kuikka, S., Maier, H. R., Rizzoli, A. E., van Delden, H., & Voinov, A. A. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management <<https://doi.org/10.1016/j.envsoft.2013.05.005>>. *Environmental Modelling & Software*, 47, 159–181.
- Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making <<https://doi.org/10.1016/j.envsoft.2017.06.054>>. *Environmental Modelling & Software*, 96, 239–250.
- Krysanova, V., & Arnold, J. G. (2008). Advances in ecohydrological modelling with SWAT—A review <<https://doi.org/10.1623/hysj.53.5.939>>. *Hydrological Sciences Journal*, 53(5), 939–947.
- Lane, D. C. (1999). Social theory and system dynamics practice <[https://doi.org/10.1016/S0377-2217\(98\)00192-1](https://doi.org/10.1016/S0377-2217(98)00192-1)>. *European Journal of Operational Research*, 113(3), 501–527.
- Leemhuis, C., Jung, G., Kasei, R., & Liebe, J. (2009). The Volta Basin Water Allocation System: Assessing the impact of small-scale reservoir development on the water resources of the Volta basin, West Africa <<https://doi.org/10.5194/adgeo-21-57-2009>>. *Advances in Geosciences*, 21, 57–62.
- Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the next one hundred years: New methods for quantitative, long-term policy analysis* <https://www.rand.org/pubs/monograph_reports/MR1626.html>. RAND Corporation.
- Letcher, R. (2005). *Implementation of a water allocation decision support system in the Namoi and Gwydir valleys*. Paper presented at MODSIM 2005 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, Canberra, Australia.
- Letcher, R. A., Croke, B. F., & Jakeman, A. J. (2007). Integrated assessment modelling for water resource allocation and management: A generalised conceptual framework. *Environmental Modelling & Software*, 22(5), 733–742.
- Li, X., Cheng, G., Lin, H., Cai, X., Fang, M., Ge, Y., Hu, X., Chen, M., & Li, W. (2018). Watershed system model: The essentials to model complex human-nature system at the river basin scale <<https://doi.org/10.1002/2017JD028154>>. *Journal of Geophysical Research: Atmospheres*, 123(6), 3019–3034.
- Little, J. C., Hester, E. T., ElSawah, S., Filz, G. M., Sandu, A., Carey, C. C., Iwanaga, T., & Jakeman, A. J. (2019). A tiered, system-of-systems modeling framework for resolving complex socio-environmental policy issues <<https://doi.org/10.1016/j.envsoft.2018.11.011>>. *Environmental Modelling & Software*, 112, 82–94.
- Liu, Y., Mahmoud, M., Hartmann, H., Stewart, S., Wagener, T., Semmens, D., Stewart, R., Gupta, H., Dominguez, D., Hulse, D., Letcher, R., Rashleigh, B., Smith, C., Street, R., Ticehurst, J., Twery, M., van Delden, H., & White, D. (2008). Formal scenario development for environmental impact assessment studies <<https://doi.org/10.1016/>

- [S1574-101X\(08\)00609-1](#)>. In A. J. Jakeman, A. A. Voinov, A. E. Rizzoli, & S. H. Chen (Eds.), *Developments in integrated environmental assessment* (Vol. 3, pp. 145–162). Elsevier.
- Loucks, D. P., & Van Beek, E. (2017). *Water resource systems planning and management: An introduction to methods, models, and applications*. Springer.
- Lubell, M., & Edelenbos, J. (2013). Integrated water resources management: A comparative laboratory for water governance. *International Journal of Water Governance*, 1(3–4), 177–196.
- Ma, L., He, C., Bian, H., & Sheng, L. (2016). MIKE SHE modeling of ecohydrological processes: Merits, applications, and challenges <https://doi.org/10.1016/j.ecoleng.2016.01.008>>. *Ecological Engineering*, 96, 137–149.
- Madni, A. M., & Sievers, M. (2014). Systems integration: Key perspectives, experiences, and challenges <https://doi.org/10.1002/sys.21249>>. *Systems Engineering*, 17(1), 37–51.
- Maier, H. R., Guillaume, J. H. A., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environmental Modelling & Software*, 81, 154–164.
- Malafant, K. W. J., & Fordham, D. P. (1970). GIS, DSS and integrated scenario modelling frameworks for exploring alternative futures. *WIT Transactions on Ecology and the Environment*, 22, 669–678.
- Mannik, R., Boronkay, A., Jordan, P., Church, T., Hughes, D., & Blockwell, S. (2012). Applying eWater source as the catchment model for the Hawkesbury-Nepean water quality model system <https://search.informit.org/doi/10.3316/informit.907677745040901>>. In *Hydrology and Water Resources Symposium 2012* (pp. 645–655). Engineers Australia.
- Marchau, V. A., Walker, W. E., Bloemen, P. J., & Popper, S. W. (Eds.). (2019). *Decision making under deep uncertainty: From theory to practice* <https://library.oapen.org/handle/20.500.12657/22900>> (p. 405). Springer Nature.
- McDonald, M. G., & Harbaugh, A. W. (1984). *A modular three-dimensional finite-difference ground-water flow model* <https://doi.org/10.3133/twri06A1>> (Open-File Report 83–875). U.S. Geological Survey.
- McKinney, D. C., Cai, X., Rosegrant, M. W., & Scott, C. A. (1999). *Modeling water resources management at the basin level: Review and future directions* (SWIM Paper 6). International Water Management Institute.
- MDBA. (2016). *Towards a healthy, working Murray–Darling Basin—Basin Plan annual report 2015–16* <https://www.mdba.gov.au/report/basin-plan-annual-report-2015-16>> (Annual Report No. 04/17; p. 52).
- MDBA. (2020). *Trends in water use relative to the sustainable diversion limit in the Southern Murray Darling Basin—Final report* <https://www.mdba.gov.au/sites/default/files/pubs/trends-in-water-use-relative-to-the-sustainable-diversion-limit%28SDL%29-in-the-southern-murray-darling-basin-2020-full-report.pdf>> (No. 61/20; p. 115).
- Menton, M., Larrea, C., Latorre, S., Martinez-Alier, J., Peck, M., Temper, L., & Walter, M. (2020). Environmental justice and the SDGs: From synergies to gaps and contradictions <https://doi.org/10.1007/s11625-020-00789-8>>. *Sustainability Science*, 15(6), 1621–1636.
- Mirchi, A., Watkins, D., Jr., & Madani, K. (2010). Modeling for watershed planning, management, and decision making. In J. C. Vaughn (Ed.), *Watersheds: Management, restoration and environmental impact* (pp. 1–25). Nova Science Publishers.

- Molle, F. (2009). River-basin planning and management: The social life of a concept <https://doi.org/10.1016/j.geoforum.2009.03.004>. *Geoforum*, 40(3), 484–494.
- Mostert, E., Craps, M., & Pahl-Wostl, C. (2008). Social learning: The key to integrated water resources management? <https://doi.org/10.1080/02508060802275757> *Water International*, 33(3), 293–304.
- National Academies of Science, Engineering, and Medicine. (2021). *Next generation earth systems science at the National Science Foundation* <https://doi.org/10.17226/26042>. National Academies Press.
- O'Neill, R., Burns, K., Hameed, T., & Roberts, S. (2009). *Macquarie River Valley. IQQM Cap implementation summary report. Issue: 2* https://www.industry.nsw.gov.au/_data/assets/pdf_file/0006/353643/macquarie-river-valley-iqqm-cap-implementation-summary-report.pdf (p. 132). Department of Environment, Climate Change and Water, NSW Government, Office of Water.
- Osman, I. H., & Laporte, G. (1996). Metaheuristics: A bibliography <https://doi.org/10.1007/BF02125421>. *Annals of Operations Research*, 63(5), 511–623.
- O'Sullivan, J., Pollino, C., Taylor, P., Sengupta, A., & Parashar, A. (2020). An integrative framework for stakeholder engagement using the Basin Futures Platform. *Water*, 12(9), 2398.
- Pahl-Wostl, C., & Hare, M. (2004). Processes of social learning in integrated resources management <https://doi.org/10.1002/casp.774>. *Journal of Community & Applied Social Psychology*, 14(3), 193–206.
- Pahl-Wostl, C., Sendzimir, J., Jeffrey, P., Aerts, J., Berkamp, G., & Cross, K. (2007). Managing change toward adaptive water management through social learning <http://www.jstor.org/stable/26267877>. *Ecology and Society*, 12(2), 1–18.
- Palmer, M. A. (2012). Socioenvironmental sustainability and actionable science <https://doi.org/10.1525/bio.2012.62.1.2>. *BioScience*, 62(1), 5–6.
- Pande, S., & Sivapalan, M. (2017). Progress in socio-hydrology: A meta-analysis of challenges and opportunities <https://doi.org/10.1002/wat2.1193>. *WIREs Water*, 4(4), e1193.
- Paredes-Arquiola, J., Solera, A., Martinez-Capel, F., Momblanch, A., & Andreu, J. (2013). Integrating water management, habitat modelling and water quality at the basin scale and environmental flow assessment: Case study of the Tormes River, Spain <https://doi.org/10.1080/02626667.2013.821573>. *Hydrological Sciences Journal*, 59(3–4), 878–889.
- Perera, B. J. C., James, B., & Kularathna, M. D. U. (2005). Computer software tool REALM for sustainable water allocation and management <https://doi.org/10.1016/j.jenvman.2005.06.014>. *Journal of Environmental Management*, 77(4), 291–300.
- Perrings, C. (2006). Resilience and sustainable development <https://doi.org/10.1017/S1355770X06003020>. *Environment and Development Economics*, 11(4), 417–427.
- Pittock, J. (2013). Lessons from adaptation to sustain freshwater environments in the Murray–Darling Basin, Australia <https://doi.org/10.1002/wcc.230>. *WIREs Climate Change*, 4(5), 429–438.
- Prosser, I., Crossman, N., Mahoney, J., Rustomji, P., Chen, Y., Brown, A., Robson, B., Sherman, B., Sims, N., & Jolly, I. (2012). *Assessment of the ecological and economic benefits of environmental water in the Murray–Darling Basin: The*

- final report to the Murray–Darling Basin Authority from the CSIRO Multiple Benefits of the Basin Plan Project <https://doi.org/10.4225/08/584af4c32c941>.
- Razavi, S., Tolson, B. A., & Burn, D. H. (2012). Review of surrogate modeling in water resources <https://doi.org/10.1029/2011WR011527>. *Water Resources Research*, 48(7).
- Refsgaard, J. C., & Storm, B. (1995). MIKE SHE. In V. P. Singh (Ed.), *Computer models of watershed hydrology* (pp. 809–846). Water Resources Publications.
- Reichert, M., & Weber, B. (2012). *Enabling flexibility in process-aware information systems: Challenges, methods, technologies*. Springer Science & Business Media.
- Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model <https://doi.org/10.1145/37401.37406>. *ACM SIGGRAPH Computer Graphics*, 21(4), 25–34.
- Riley, J. P., & Averett, D. (1970). Systems Analysis of Hydrologic Problems https://digitalcommons.usu.edu/water_rep/128. *Reports*. Paper 128.
- Ross, A., & Connell, D. (2016). The evolution and performance of river basin management in the Murray–Darling Basin <https://www.jstor.org/stable/26269970>. *Ecology and Society*, 21(3).
- Rubin, D. B. (1976). Inference and missing data <https://doi.org/10.1093/biomet/63.3.581>. *Biometrika*, 63(3), 581–592.
- Sabatier, P. A. (1986). Top-down and bottom-up approaches to implementation research: A critical analysis and suggested synthesis <https://doi.org/10.1017/S0143814X00003846>. *Journal of Public Policy*, 6 (1), 21–48.
- Saleem, S., Levison, J., Parker, B., Martin, R., & Persaud, E. (2020). Impacts of climate change and different crop rotation scenarios on groundwater nitrate concentrations in a sandy aquifer <https://doi.org/10.3390/su12031153>. *Sustainability*, 12(3), 1153.
- Schelling, T. C. (1971). Dynamic models of segregation <https://doi.org/10.1080/0022250X.1971.9989794>. *The Journal of Mathematical Sociology*, 1(2), 143–186.
- Schoemaker, P. J. H. (1982). The expected utility model: Its variants, purposes, evidence and limitations <https://www.jstor.org/stable/2724488>. *Journal of Economic Literature*, 20(2), 529–563.
- Schwab, K. (2016). *The Fourth Industrial Revolution: What it means, how to respond* <https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/> [Web article]. World Economic Forum.
- Sieber, J. (2006). *WEAP water evaluation and planning system* <https://scholarsarchive.byu.edu/cgi/viewcontent.cgi?article=3544&context=iemssconference>. Paper presented at the 3rd International Congress on Environmental Modelling and Software, Burlington, VT, United States.
- Simons, M., Podger, G., & Cooke, R. (1996). IQQM—A hydrologic modelling tool for water resource and salinity management [https://doi.org/10.1016/S0266-9838\(96\)00019-6](https://doi.org/10.1016/S0266-9838(96)00019-6). *Environmental Software*, 11(1), 185–192.
- Singh, R., Subramanian, K., & Refsgaard, J. C. (1999). Hydrological modelling of a small watershed using MIKE SHE for irrigation planning [https://doi.org/10.1016/S0378-3774\(99\)00022-0](https://doi.org/10.1016/S0378-3774(99)00022-0). *Agricultural Water Management*, 41(3), 149–166.

- Solomon, S., Manning, M., Marquis, M., & Qin, D. (2007). *Climate change 2007—The physical science basis: Working group I contribution to the fourth assessment report of the IPCC* <<https://www.ipcc.ch/report/ar4/wg1/>> (Vol. 4). IPCC.
- Soncini-Sessa, R., Castelletti, A., & Weber, E. (2007). *Integrated and participatory water resources management-theory*. Elsevier.
- Sperotto, A., Molina, J. L., Torresan, S., Critto, A., Pulido-Velazquez, M., & Marcomini, A. (2019). Water quality sustainability evaluation under uncertainty: A multi-scenario analysis based on Bayesian networks <<https://doi.org/10.3390/su11174764>>. *Sustainability*, 11(17), 4764.
- Subramanian, N., & Jeyaraj, A. (2018). Recent security challenges in cloud computing <<https://doi.org/10.1016/j.compeleceng.2018.06.006>>. *Computers & Electrical Engineering*, 71, 28–42.
- Sun, A. (2013). Enabling collaborative decision-making in watershed management using cloud-computing services <<https://doi.org/10.1016/j.envsoft.2012.11.008>>. *Environmental Modelling & Software*, 41, 93–97.
- Taylor, P., Rahman, J., O’Sullivan, J., Podger, G., Rosello, C., Parashar, A., Sengupta, A., Perraud, J.-M., Pollino, C., & Coombe, M. (2021). Basin futures, a novel cloud-based system for preliminary river basin modelling and planning <<https://doi.org/10.1016/j.envsoft.2021.105049>>. *Environmental Modelling & Software*, 141, 105049.
- Todini, E. (2011). History and perspectives of hydrological catchment modelling <<https://doi.org/10.2166/nh.2011.096>>. *Hydrology Research*, 42(2–3), 73–85.
- Vogel, R. M., Lall, U., Cai, X., Rajagopalan, B., Weiskel, P. K., Hooper, R. P., & Matalas, N. C. (2015). Hydrology: The interdisciplinary science of water <<https://doi.org/10.1002/2015WR017049>>. *Water Resources Research*, 51(6), 4409–4430.
- Voinov, A., Jenni, K., Gray, S., Kolagani, N., Glynn, P. D., Bommel, P., Prell, C., Zellner, M., Paolisso, M., Jordan, R., Sterling, E., Schmitt Olabisi, L., Giabbanelli, P. J., Sun, Z., Le Page, C., Elsawah, S., BenDor, T. K., Hubacek, K., Laursen, B. K., . . . Smajgl, A. (2018). Tools and methods in participatory modeling: Selecting the right tool for the job <<https://doi.org/10.1016/j.envsoft.2018.08.028>>. *Environmental Modelling & Software*, 109, 232–255.
- Von Bertalanffy, L. (1950). An outline of general system theory <<https://doi.org/10.1093/bjps/l.2.134>>. *British Journal for the Philosophy of Science*, 1, 134–165.
- Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or perish: A review of planning approaches for adaptation under deep uncertainty <<https://doi.org/10.3390/su5030955>>. *Sustainability*, 5(3), 955–979.
- Walker, W. E., Marchau, V. A., & Swanson, D. (2010). Addressing deep uncertainty using adaptive policies: Introduction to section 2. *Technological Forecasting and Social Change*, 77(6), 917–923.
- Weber, L. J., Muste, M., Bradley, A. A., Amado, A. A., Demir, I., Drake, C. W., Krajewski, W. F., Loeser, T. J., Politano, M. S., Shea, B. R., & Thomas, N. W. (2018). The Iowa Watersheds Project: Iowa’s prototype for engaging communities and professionals in watershed hazard mitigation <<https://doi.org/10.1080/15715124.2017.1387127>>. *International Journal of River Basin Management*, 16(3), 315–328.
- Wheater, H., Jakeman, A., & Beven, K. (1993). Progress and directions in rainfall-runoff modelling. In A. J. Jakeman, M. B. Beck & M. J. McAleer (Eds.), *Modeling change in environmental systems* (pp. 101–132). Wiley.

Whittington, J., Cottingham, P., Gawne, B., Hillman, T., Thoms, M., & Walker, K. (2000). Ecological sustainability of rivers of the Murray–Darling Basin. *Review of Operation of the Cap: Overview Report of the Murray–Darling Basin Commission. Cooperative Research Centre for Freshwater Ecology*. Murray–Darling Basin Ministerial Council.

Winsberg, E. (2010). *Science in the age of computer simulation*. University of Chicago Press.

Wu, H., Zhang, L., & Zhang, X. (2019). Cloud data and computing services allow regional environmental assessment: A case study of Macquarie–Castlereagh Basin, Australia <https://doi.org/10.1007/s11769-019-1040-4>. *Chinese Geographical Science*, 29(3), 394–404.

Zagona, E. (2016). RiverWare model and analysis tools for river system planning and management <https://www.colorado.edu/cadswes/riverware-model-and-analysis-tools-river-system-planning-and-management>. In *Proceedings of the Seventh Graduate Studies and Scientific Research Conference in Basic and Engineering Sciences*. University of Colorado.

Zagona, E. A., Fulp, T. J., Shane, R., Magee, T., & Goranflo, H. M. (2001). Riverware: A generalized tool for complex reservoir system modeling <https://doi.org/10.1111/j.1752-1688.2001.tb05522.x>. *Journal of the American Water Resources Association*, 37 (4), 913–929.

Zavestoski, S., & Swarnakar, P. (2017). Neither “top-down” nor “bottom-up”: A “middle-out” alternative to sustainable development. In P. Swarnakar, S. Zavestoski, & B. K. Pattnaik (Eds.), *Bottom-up approaches in governance and adaptation for sustainable development: Case studies from India and Bangladesh* (pp. 315–325). SAGE.

Zhao, H., Zhang, J., James, R., & Laing, J. (2012). Application of MIKE SHE/MIKE 11 model to structural BMPs in S191 Basin, Florida. *Journal of Environmental Informatics*, 19(1), 10–19.