AGU PUBLICATIONS

JGR

Journal of Geophysical Research: Atmospheres

COMMENTARY

10.1002/2017JD028154

Special Section:
Water-soil-air-plant-human nexus: Modeling and observing complex land-surface systems at river basin scale

Key Points:
- A watershed system model should represent the coevolution of the water-land-air-plant-human nexus
- A new approach to build a scientifically based decision support system can take advantage of surrogate modeling
- Darwinian approaches and soft systems methodology will be critical in future watershed modeling

Correspondence to:
X. Li,
lixin@lzb.ac.cn

Citation:
Li, X., Cheng, G., Lin, H., Cai, X., Fang, M., Ge, Y., et al. (2018). Watershed system model: The essentials to model complex human-nature system at the river basin scale. *Journal of Geophysical Research: Atmospheres*, *123*, 3019–3034. https://doi.org/10.1002/2017JD028154

Received 3 DEC 2017
Accepted 26 FEB 2018
Accepted article online 4 MAR 2018
Published online 25 MAR 2018

©2018. American Geophysical Union.
All Rights Reserved.

Watershed System Model: The Essentials to Model Complex Human-Nature System at the River Basin Scale

Xin Li[1,2], Guodong Cheng[3,4], Hui Lin[5], Ximing Cai[6], Miao Fang[3], Yingchun Ge[3], Xiaoli Hu[3], Min Chen[5,7], and Weiyue Li[4]

[1]Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing, China, [2]CAS Center for Excellence in Tibetan Plateau Earth Sciences, Chinese Academy of Sciences, Beijing, China, [3]Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences, Lanzhou, China, [4]Institute of Urban Studies, Shanghai Normal University, Shanghai, China, [5]Institute of Space and Earth Information Science, Chinese University of Hong Kong, Hong Kong, [6]Ven Te Chow Hydrosystems Laboratory, Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, USA, [7]Key Laboratory of Virtual Geographic Environment, Ministry of Education of China, Nanjing Normal University, Nanjing, China

Abstract Watershed system models are urgently needed to understand complex watershed systems and to support integrated river basin management. Early watershed modeling efforts focused on the representation of hydrologic processes, while the next-generation watershed models should represent the coevolution of the water-land-air-plant-human nexus in a watershed and provide capability of decision-making support. We propose a new modeling framework and discuss the know-how approach to incorporate emerging knowledge into integrated models through data exchange interfaces. We argue that the modeling environment is a useful tool to enable effective model integration, as well as create domain-specific models of river basin systems. The grand challenges in developing next-generation watershed system models include but are not limited to providing an overarching framework for linking natural and social sciences, building a scientifically based decision support system, quantifying and controlling uncertainties, and taking advantage of new technologies and new findings in the various disciplines of watershed science. The eventual goal is to build transdisciplinary, scientifically sound, and scale-explicit watershed system models that are to be codesigned by multidisciplinary communities.

1. Introduction

Earth system modeling, a basic research method for Earth system science, is regarded as the second Copernican revolution (Schellnhuber, 1999). Modeling can be considered a synthesis approach to formalizing existing knowledge of Earth system science. Numerical modeling is the only means of simulating the evolution and interactions among the spheres of the complex and giant Earth system. Through numerical modeling, the qualitative conceptualization of the Earth system can be converted into a quantitative understanding. Models are capable of reproducing the past state and forecasting the future state of the Earth system. Moreover, models can help researchers, stakeholders, and decision makers propose countermeasures in advance of possible changes in the future based on real and hypothetical scenarios. In this regard, numerical modeling is also an indispensable tool for achieving sustainability (Reid et al., 2010; Weaver et al., 2013).

Watersheds are a basic unit of Earth's land-surface system (Cheng, 2009; Cheng & Li, 2015). Therefore, a watershed model can be considered a basin-scale Earth system model designed for understanding complex watershed systems and for supporting integrated river basin management. Similar to Earth system models, the simulation of energy, water, and geochemical cycles of the natural system is a necessity in watershed modeling. Additionally, a watershed model must be sufficiently detailed because the scale of watershed studies is much smaller than that used for the entire Earth system. Many processes that are not considered in global-scale models, such as three-dimensional groundwater dynamics, the heterogeneity of the vegetation distribution, land use seasonality, and water uses, must be presented in a watershed model. Additionally, a watershed model should include the simulation of human activities to understand human footprints on hydrologic and ecological processes and to develop solutions for river basin management. The key idea behind watershed modeling is the development of an integrated model for the water-land-air-plant-human nexus (Cheng et al., 2014). The elements simulated include surface water, groundwater, water uses (e.g., irrigation), water quality, land cover/land use change, soil erosion, energy balance, vegetation dynamics, crop growth, carbon and nitrogen cycles, water resource management, and the watershed socioeconomic processes.

The research on integrated watershed modeling is becoming active. Some well-known integrated watershed models have been developed, that is, the Soil and Water Assessment Tool (SWAT) and its variants (Arnold & Fohrer, 2005; Gassman et al., 2007), the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) developed by the United States Environmental Protection Agency (EPA, 2001), the coupled Groundwater and Surface-water Flow model (GSFLOW) (Markstrom et al., 2008), ParFlow (Kollet & Maxwell, 2006), MIKE SHE (Système Hydrologique Européen) and MIKE BASIN developed by the Denmark Hydrological Research Institute (DHI, 2003; Graham & Butts, 2005), and the HydroGeoSphere (Brunner & Simmons, 2012). Typically, these models or software tools are geared toward hydrology. These models employ a distributed hydrological model or a groundwater model as the basic framework, while other models/modules can be added. In recent years, many attempts have been made to couple land surface models (Niu et al., 2014; Wang, Koike, et al., 2010), dynamic vegetation and crop growth models (Li, Zhou, et al., 2013), carbon and nitrogen cycle models (Tian et al., 2012), land use models (Ray et al., 2012), and economic models (Cai, 2008; Cai, McKinney, & Lasdon, 2003; Voinov et al., 1999) to distributed hydrological models. However, bidirectionally coupling a regional climate model with distributed hydrological and ecological models is rare (Adam et al., 2014; Larsen et al., 2014; Wagner et al., 2016). To couple a climate model to a full land-surface model that includes energy, water and biogeochemical cycles, land use dynamics, and social-economic processes is challenging. To our knowledge, at present, there is no integrated watershed model that can fully simulate the water-land-air-plant-human nexus.

Another important aspect of watershed model integration is the development and application of the modeling environment. The modeling environment can improve the modeling efficiency and model-data integration, facilitate model intercomparison, model selection, and model-human interactions, and support rapid customization of a decision support system (DSS) (Argent, 2004; Dolk, 1993; Granell et al., 2013; Laniak et al., 2013). In the context of Earth system science, the development of a modeling environment has been highly valued; for example, the Earth System Modeling Framework (ESMF) (Hill et al., 2004), Grid Enabled Integrated Earth System Model (GENIE) (Price et al., 2005), Land Information System (Kumar et al., 2006), the Modular Earth Submodel System (MESSy) (Jöckel et al., 2005), the OASIS3 coupler (Valcke, 2013), and other platforms have been developed to provide a unified software platform for Earth system modeling and to couple weather, climate, and related models (Valcke et al., 2016). In the field of environment modeling, mature modeling environments have been developed since the 1980s, including the modular modeling system (MMS) (Leavesley et al., 1996), the spatial modeling environment (SME) (Maxwell & Costanza, 1997), the open modeling interface (OpenMI) (Castronova and Goodall, 2013; Gregersen et al., 2007; Knapen et al., 2013), the invisible modeling environment (TIME) (Argent et al., 2009), and the Open Modeling System (OMS) (David et al., 2013). These software tools have facilitated the rapid increase in integrated environmental modeling.

This study presents visionary concepts for integrated watershed modeling. Based on our understanding of the requirements of watershed science and integrated river basin management, we outline the model components of a watershed system model that together can simulate the feedbacks involved in water-land-air-plant-human nexus and the coevolution of the coupled human-nature system. We then discuss the key techniques of and current challenges in developing watershed system models. Finally, we provide some prospects for future research directions.

2. Vision of a Watershed System Model

2.1. Components of a Watershed System Model

A watershed system model simulates both the natural and human systems of a watershed and the interactions between different components of the human-nature system. Modeling natural systems usually involves hydrology, ecology, meteorology, land surface science, cryospheric science, and other natural science disciplines. Modeling human systems involves land use, sociology, economics, eco-economics/hydro-economics, and other social science disciplines (Cai, McKinney, & Lasdon, 2003; Cheng & Li, 2015; McKinney et al., 1999).

Quantitative models have been developed in all of these fields. However, model integration is not necessarily straightforward. All of the models are built for different purposes, with significantly different modeling approaches, spatial and temporal scales, and computational costs. The maturity of these models also varies greatly. Therefore, coupling these models is a grand challenge from both the scientific and technical perspectives. In Table 1, we briefly summarize the models proposed for full or partial inclusion in a watershed system model. We focus on the model properties related to coupling and neglect the introduction of model functions and applications.

By comparing the models listed in Table 1, the modeling of traditional fields, such as surface and groundwater flow, land surface energy and water cycles, and the economy, is relatively highly mature. The modeling of ecosystem dynamics, specifically vegetation growth, biogeochemical cycles, and land-use and land-cover change, is in medium maturity. The modeling in some new fields, such as ecosystem service valuation, remains an "imperfect art" (Harou et al., 2009). The modeling approach to natural systems is dominated by system dynamics; however, there is a transformative trend toward using agent-based models (ABMs) (Bousquet & Le Page, 2004; Matthews et al., 2007), cellular automata, and data-driven approaches in modeling the ecosystem and human systems. A common feature of these models listed in Table 1 is that most of them are complex, overparameterized, and have very large uncertainties; therefore, controlling and reducing uncertainty is a necessity in integrated modeling.

2.2. Aims of Integrated Watershed Modeling

Integrated watershed modeling is significant to both fundamental and applied science because watershed science aims to understand complex watershed behaviors according to fundamental science and aims to serve integrated river basin management according to applied science (Cheng & Li, 2015; McKinney et al., 1999; Mirchi et al., 2010). To achieve these aims, two types of integrated system need to be developed.

The first type of integrated system is for scientific purposes and is a localization of an Earth system model at the river basin scale; it acts as a comprehensive model of the water-ecosystem-economy system at the river basin scale. This watershed system model, according to our vision, includes the following components, at minimum:

1. A distributed hydrological model that is fully coupled with a groundwater model and absorbs useful features (e.g., physical model of evapotranspiration) from land surface models and frameworks the watershed system model;
2. Vegetation and crop growth models that simulate ecosystem dynamics and models that simulate key biogeochemical cycles, such as the carbon cycle;
3. A regional climate model that can be bidirectionally coupled with the surface models to investigate the land-atmosphere interaction or used in the downscaling to generate high-resolution atmospheric forcing for the surface models;
4. Other natural process models, for example, glacier dynamics, snowmelt, and freeze-thaw cycle models, that can be coupled to the integrated model when necessary;
5. A water resource model that simulates the allocation and redistribution of water by dams, irrigation infrastructures, and management policies;
6. Environmental-economic models, particularly hydro-economic, eco-economic, and water trade models that simulate water and ecosystem-related economic activities, coupled with the above natural system models to generate a watershed system model with the ability to comprehensively simulate the interactions between the environmental and economic systems of the watershed; and
7. Societal models, for example, sociohydrologic models, in which the technical, institutional, and behavioral evolution as well as the change in norms and values are considered as endogenous parts of the hydrological cycle (Sivapalan, Savenije, & Blöschl, 2012; Wei et al., 2017).

The second type of integrated system is for management purposes. In this case, the aim is to build a scientific-model-based spatially explicit DSS for integrated river basin management. The DSS, according to our vision, incorporates the following components:

1. Surrogates of the first type of watershed system model described above, which can be a lower-fidelity surrogate simplified from the physical model or a response surface high-fidelity surrogate;
2. Decision-making algorithms and group decision-making tools;

10.1002/2017JD028154

Table 1
Disciplinary Models to be Coupled to a Watershed System Model

Model	Maturity	Modeling approach	Complexity	Treatment of space	Treatment of time	Uncertainty	Computational cost	Typical models
Distributed hydrological model	High	Dynamic simulation	From simple to overly complex	Hydrological response unit, regular grid	Hourly to daily	Large; parameter calibration is necessary	Depends on model structure and spatial domain, usually large	TOPMODEL, SHE, DHSVM, SWAT, VIC, GeoTOP, GBHM
Groundwater model or integrated surface water-groundwater model	Very high	Dynamic simulation	Physical structure is simple (with a few parameters) but computation is complex	3-D model, use regular or irregular grid for spatial discretization	Daily	Large; depends on parameters and boundary conditions	Very large	MODFLOW, FEFLOW, GSFLOW, ParFlow, HEIFLOW
Land surface model	High for energy and water cycle components	Dynamic simulation	Some are overparameterized	1-D model	Hourly to daily	Very large	Moderate	BATS, SiB2, Noah, LSM, CLM
Vegetation dynamics/crop growth model	Medium to high, depending on the plant or crop type	Dynamic simulation, L-systems, and models that incorporate genetic regulatory networks	Overparameterized	1-D model or use patch (vegetation-type-dependent) as a modeling unit	Daily	Large; parameter calibration is necessary	Moderate	IBIS, BIOME3, LPJ-DGVM, DSSAT, WOFOST, APSIM
Biogeochemical cycle	High for carbon model but medium or low for other biogeochemical cycles	Dynamic simulation	Empirically based but overparameterized	1-D model	Daily	Large; parameter calibration is necessary	Moderate	TEM, DNDC
Land use /land cover model	Medium	Dynamic simulation; cellular automata; ABM	Moderate	Patches	Yearly	Capable of capturing the pattern, difficult to realize the true evolution	Moderate	CLUE-S, Simland, SprawlSim
Water resource management model	High	ABM	Model mechanism is simple but model structure could be complex	Node-link topology	Daily, weekly, monthly, yearly	Low	Low	Water resource management algorithms are usually coupled into hydrological, groundwater, or land surface models (Nazemi & Wheater, 2015a, 2015b)
Trade model, particularly virtual water	Medium	Input-output model	Model mechanism is simple	Administrative unit or irrigation district	Monthly to yearly	Large	Low	Input-output model
Ecosystem service valuation model	Early stage	Evaluation model	Model mechanism is simple	Ecosystem type is the basic unit	Yearly	Very large	Low	InVEST, ARIES, SolVES, MIMES
Economic model (ecological-economic, water-economic, hydro-economic)	High	Dynamic simulation; ABM; input-output model; CGE	Moderate	Administrative unit or irrigation district	Monthly to yearly	Medium	Low	Input-output model, CGE

Note. ABM = agent-based model; APSIM = Agricultural Production Systems SIMulator; ARIES = Artificial Intelligence for Ecosystem Services; BATS = Biosphere Atmosphere Transfer Scheme; CGE = computable general equilibrium; CLM = Community Land Model; CLUE-S = Conversion of Land Use and its Effects at Small Region Extent; DHSVM = Distributed Hydrology Soil Vegetation Model; DNDC = DeNitrification and DeComposition; DSSAT = Decision Support System for Agrotechnology Transfer; GBHM = geomorphologically based distributed hydrological model; GSFLOW = coupled Groundwater and Surface-water Flow model; IBIS = Integrated Biosphere Simulator; InVEST = Integrated Valuation of Ecosystem Services and Trade-offs; LPJ-DGVM = Lund-Potsdam-Jena Dynamic Global Vegetation Model; LSM = Land Surface Model; MIMES = Multiscale Integrated Models of Ecosystem Services; SHE = System Hydrologic European; SiB2 = Simple Biosphere Model 2; SolVES = Social Values for Ecosystem Services; SWAT = Soil and Water Assessment Tool; TEM = Terrestrial Ecosystem Model; VIC = Variable Infiltration Capacity; WOFOST = World Food Studies.

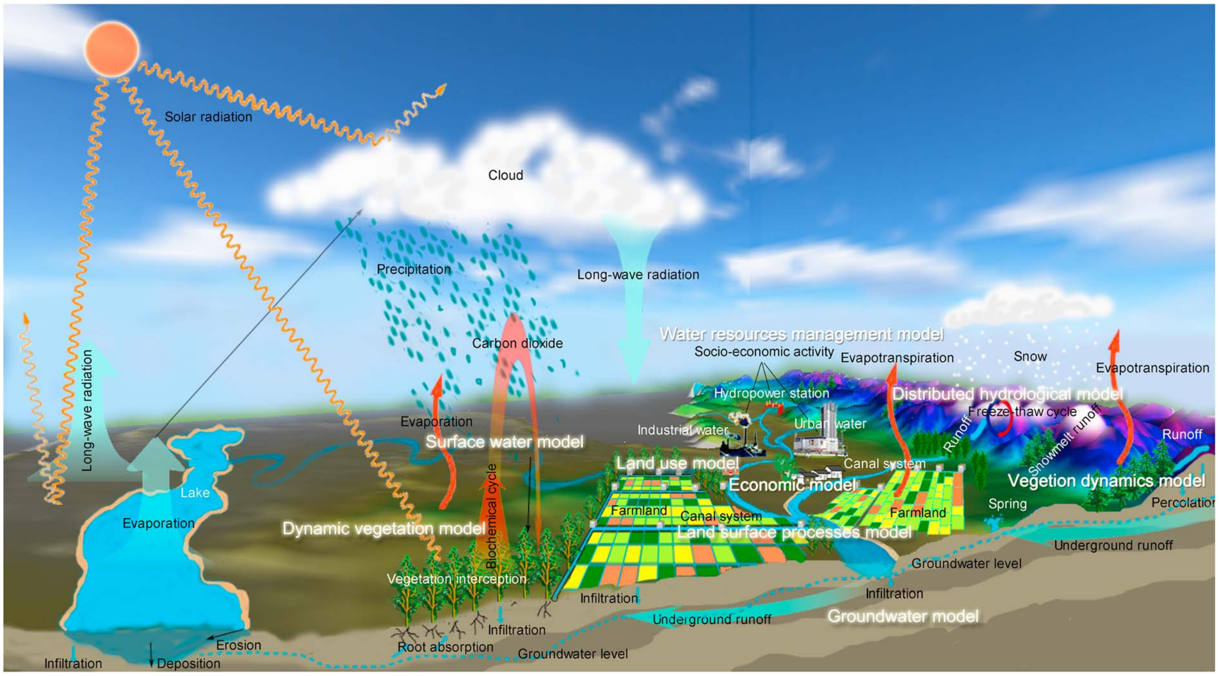

Figure 1. Vision of a watershed system model.

3. Groupware to facilitate human-human and human-computer interactions; and
4. Tools for data management, scenario generation, and visualization.

Figure 1 illustrates our vision of a watershed system model. We use the Heihe River basin, which is a typical inland river basin in northwest China and serves as a testbed for integrated watershed studies in China (Cheng et al., 2014; Li, Cheng, et al., 2013; Li et al., 2018), as an example. This river basin can be naturally divided into an upstream mountainous area and a midstream and downstream plains area. In the mountainous area, a distributed hydrological model is used as the framework model; then, ecological models, such as forest, grassland, and wetland dynamics models and carbon cycle models were added. Because cryospheric processes dominate ecohydrological processes in winter, we attempted to add cryospheric process modules, including glacier melt, snowmelt, and frozen soil hydrology, to the distributed hydrological model (Gao et al., 2016; Qin et al., 2016; Wang, Koike, et al., 2010; Yang et al., 2015; Zhang et al., 2013, 2017; Zhou et al., 2014). The plains area presents a unique challenge because of its very thick vadose zone. Thus, the first step of building a watershed system model is to develop a fully coupled surface water-groundwater model that can address the thick vadose zone (Tian, Zheng, Wu, et al., 2015; Tian, Zheng, Zheng, et al., 2015; Wang, Ma, et al., 2010; Wu et al., 2015; Yao et al., 2015). Water use has altered the hydrological cycle; hybrid human-nature system factors, including water allocation and irrigation, are driving factors for surface water/groundwater interactions such that these processes need to be simulated in the integrated model. Furthermore, a biogeochemical cycle model, geochemical model, land use model, economic model, and even a geomorphic model are proposed as additions to the integrated model (Figure 1).

3. How to Achieve Watershed Model Integration

3.1. Model Structure

A model is structurally more complicated than data. A model structure is characterized by the model conceptualization, formalization, representation, and code. All of these elements are personally and stylistically diverse; usually, no well-recognized standard is followed. Therefore, model integration is much more difficult than data integration (Dolk & Kottemann, 1993; Kelly et al., 2013; Tang, 2001). From the perspective of computer and information sciences, the structure of a watershed model, whether a hydrological,

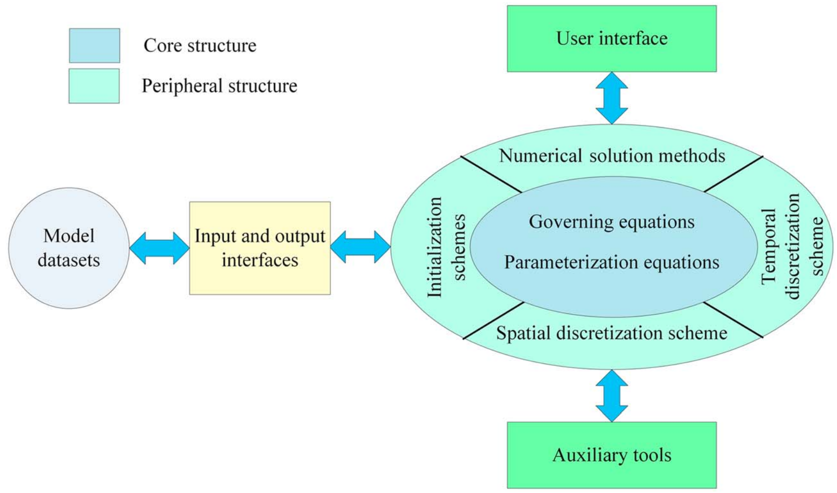

Figure 2. Structure of the watershed model from the perspective of computer and information science.

ecological, or land surface model, is composed of the physical structure, the input and output interfaces, the user interface, and auxiliary tools (Figure 2). A brief description of each of these components follows:

1. The physical structure is composed of the core structure and the peripheral structure. The core structure consists of the governing equations (usually differential equations) and parameterization equations/formulae of the model. The peripheral structure includes numerical solution methods, spatial and temporal discretization schemes, and model initialization schemes. The physical structure of the model, particularly the core structure, is a formalization of the hydrological, ecological, and socioeconomic knowledge related to the watershed. This structure is closely related to our understanding of the watershed behavior and the corresponding mathematical expressions and solutions of problems that we want to address.
2. The input-output interface (I/O interface) refers to the relationship between the model and the model data set. For watershed models, the model data set can be classified into three categories: the forcing data, which could be the near-surface atmospheric state, human activity forcing, geological settings, and other data used as boundary conditions; the model parameter data set; and the data set for the validation and diagnosis of the model (Li, Wu, et al., 2010). In general, the interface includes the input, output, preprocess, and postprocess of the above data sets. The interface, if well designed, is independent of the physical structure of the model. From a model integration viewpoint, the I/O interface is also one of the interfaces for coupling to other models or modules.
3. The user interface is an easy, efficient, and enjoyable space for users to interact with the model. The command-line interface is still common for scientific models. However, friendly graphical user interfaces and/or web-based user interfaces need to be developed.
4. Auxiliary tools, which include parameter estimation, data preparation (e.g., data interpolation, stochastic simulation (e.g., ensemble prediction), data fusion, and data conversion), data provision, visualization, and high-performance computation, can be equipped in a well-developed integrated model.

3.2. Modeling Environment and the Two Approaches for Model Integration

A narrow definition of model integration, using the concepts of the model structure defined in the above section, is to couple the model components to simulate the system. However, in a broad sense, model integration includes the development of tools to support more efficient and effective model development and enable simpler interactions between the model and data. The modeling environment, sometimes called the environmental modeling framework, realizes the broad definition of model integration and can create domain-specific models of large-scale systems (David et al., 2013; Granell et al., 2013). The model environment is a computer software platform that supports the efficient development of integrated models, the convenient coupling of existing models or modules, model management, data management and processing,

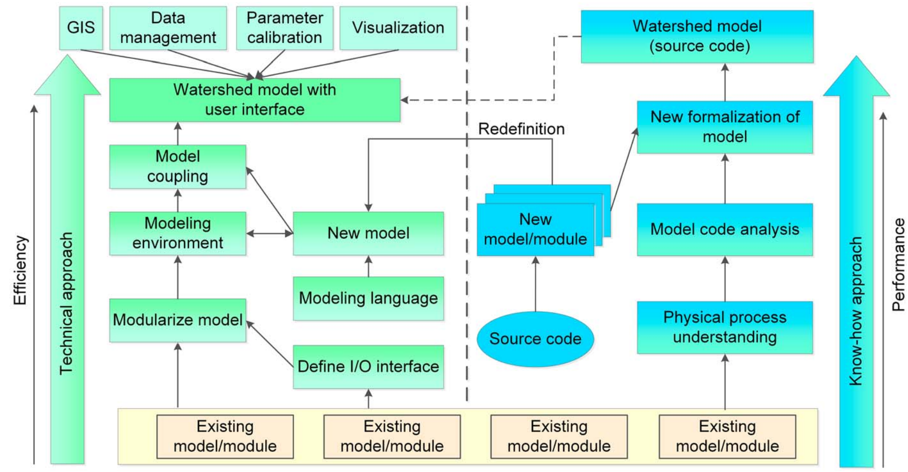

Figure 3. Know-how and technical approaches for model integration.

parameter calibration, and data and results visualization (Castronova et al., 2013; Chen et al., 2011; Cheng et al., 2014; Li, Cheng, et al., 2010; Wen et al., 2013).

Therefore, we propose that the model integration in watershed science research consists of two themes. One theme is the development of a watershed system model, which should be capable of representing the dynamics of the water-land-air-plant-human nexus. The other theme is the development of modeling environments, which focus on software support for efficient and effective model integration using advanced computational and information techniques.

To clarify the role of the modeling environment, we classify the model integration into two approaches, namely, the know-how approach and technical approach. The know-how approach is defined as the modeling approach used to formalize new understanding in the models. For example, if we use a unified equation to express the water flow in saturated and unsaturated zones, the governing equations have to be redefined. For instance, Wang used a set of unified equations to formulate the three-dimensional water movement in the vadose and saturated zones (Wang, 2007); alternatively, if a new parameterization formula is added to close a set of equations, then the numerical scheme of the model may change. In these two examples, the physical structure, particularly the core structure, of the model changes, low-level source code has to be developed, and coupling the existing modules by data transfer only is not possible. This new model development is, therefore, a multidisciplinary synthesis, and cross-field collaboration by researchers from different disciplines may be required. This type of model integration adds new knowledge to the process of integration, so it is called the know-how approach of model integration. The technical approach, in contrast, focuses on linking existing models or model components by data transfer. This approach does not modify the core structure of existing models, and it seldom modifies the peripheral structure unless some schemes, for example, the spatial and temporal discretization schemes, need to be changed. The technical approach mainly addresses the I/O interfaces, which pass data and messages among different models and model components (David et al., 2013; Gregersen et al., 2007). Overall, the technical approach falls within the scope of computer and information technologies.

Classifying the modeling approaches into know-how and technical approaches helps to clarify the relationship between the development of an integrated model and the modeling environment. As illustrated in Figure 3, the technical approach, which is usually equipped with an icon drag-and-drop function or a modeling language, is efficient for developing integrated models and promoting the integration of the model with a geographic information system, data management, parameter calibration, and visualization environments. However, the know-how approach must be used when new formalization is required or when the complexity of the new integrated model prevents the linkage of existing models/modules using only the input and output interfaces. In these cases, a new model at the level of the source code must be developed. However, the know-how approach of model integration can also benefit from the technical approach. When a new model is formulated, it can be coupled with other models/modules to form a more functional model by using the

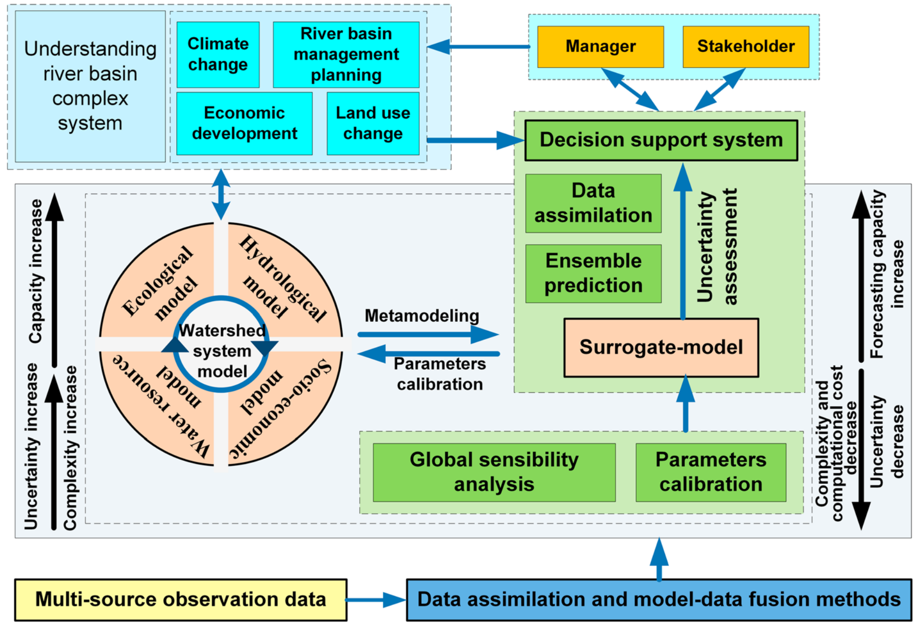

Figure 4. Relationship between the scientific model and the river basin management model.

modeling environment. Additionally, the modeling environment provides data management, parallel computation, visualization, and other necessary support for the integrated model and helps improve the model performance using various tools, such as parameter calibration.

3.3. Relationship Between a Scientific Model and River Basin Management Model

Whether a model is a tool or a hypothesis has been a subject of debate for a long time (Savenije, 2009). Our opinion is that the purpose of watershed model integration is to develop both a scientific model and a river basin management model. The scientific model, that is, the watershed system model, is used for understanding the complex processes of a river basin; thus, it is similar to a scientific hypothesis. The river basin management model is mainly applied to manage water resources, other natural resources, and socioeconomic resources; thus, it often acts as a tool. The scientific model is usually built on the basis of the existing laws of physics and is often called a mechanism model, while the watershed management model can be a completely empirical model. A scientific model is often very complex due to the complexity of watershed science, while a watershed management model mainly focuses on simplicity and usability. A scientific model does not typically need to be equipped with a graphical user interface, but a watershed management model requires a friendly user interface for easy operation. The former often involves a huge computational cost, while the latter must be computationally efficient. The former, in theory, has better predictability, but the uncertainty in the simulations is also very large and difficult to quantify. The latter is expected to inherit the predictability of the former, but uncertainty must be reduced and controlled to communicate the risks to the decision-making process.

Whether an integrated model should be simple or complex is also debated. As Albert Einstein said, "Make everything as simple as possible, but not simpler." Specifically, we should pursue the development of a simple model, but we also must ensure that the model can describe the complexity within a river basin. The balance between authenticity and simplicity is modeling art. Building a river basin management model based on a mature scientific model (Cai, Marston, & Ge, 2015; CUAHSI, 2007; Surridge & Harris, 2007) is a reflection of this aim. In Figure 4, we summarize the relationship between the two types of integrated models. The new generation of scientific models will have a large capacity, but the complexity, computational cost, and uncertainty generally increases with the increase in the extent of the model integration. To reduce and control uncertainty, we propose to apply data assimilation and other model-data fusion methods for merging multi-source observation data into the dynamics of the watershed system model. This strategy can reduce the uncertainty in the simulation and also increase the predictability of the simulations.

However, a new problem emerges; that is, watershed managers and stakeholders have difficulty using the watershed system model with a data assimilation ability because the model structure is too complex and the computational cost is too high. Although stakeholder involvement is very important, stakeholders generally do not intend to learn the complex processes behind the watershed system model. So is there a compromise between model predictability and applicability? A feasible approach may be to build a physically or computationally simplified surrogate model (Razavi, Tolson, & Burn, 2012; Wu et al., 2015, 2016) or to develop an offline data-driven surrogate model by using a huge amount of data generated from the watershed system model; in addition, it could be possible to predefine various scenarios of climate change, land use change, river basin management planning, and economic development and to conduct scenario-based simulations to support decision making. In this way, model integration could take into account both the strong predictability of a scientific model and the simplicity, robustness, applicability, and easy interaction of a management-oriented model and in the meanwhile lower the complexity and computational cost and reduce the uncertainties.

4. Challenges

4.1. Modeling the Coevolution of the Water-Land-Air-Plant-Human Nexus

One of the grand challenges in developing a watershed system model is simulating the human-nature relationship. "Research dominated by the natural sciences must transition toward research involving the full range of sciences and humanities." (Reid et al., 2010). However, fully coupled models that consider the interactions and two-way feedbacks between natural and human systems are rare. Conventionally, when modeling socioeconomic behavior, natural factors, such as water resource availability, are used as model constraints. When simulating natural systems, the potential socioeconomic changes are used to set up scenarios. In both approaches, the model states of other systems are used as exogenous variables, and the interactions and feedbacks between natural and human systems are not well represented. From a perspective of a coevolved human-nature system, the future direction is that human system states should be used as endogenous variables in the model so that the coevolution of the water-land-air-plant-human nexus can be represented (Boumans et al., 2015; Sivapalan et al., 2012, 2014; Vogel et al., 2015).

An effective approach to integrating the human and natural systems is to couple ABMs with natural system simulation models (An, 2012). This approach forms a platform that provides insight into the progressive environmental feedbacks and subsequent societal responses (Bonabeau, 2002; Smajgl et al., 2011). The use of ABMs in both the social and natural sciences has increased substantially over the last decade, moving from simple, theoretical exercises to more complex coupled social and biophysical models that describe a system; the components and the surrounding environment are predicted by coupling an ABM with a natural system model (e.g., Hu, Cai, & DuPont, 2015; Monticino et al., 2007; Ng et al., 2011; Yang et al., 2011). The challenge is to couple an ABM with a natural system model to form a cohesive, sufficiently detailed, and computationally tractable modeling framework. The coupling should be implemented using socioeconomic variables involved in both models, that is, as an indicator of behavior in the ABM and as human factors in the natural system model. The integrated model will then represent the connectedness and collective dynamics of adaptive natural and human systems with emergent behaviors rooted in local agents and mediated through levels of interaction and aggregation.

The spatial and temporal scale issues in integrating/coupling natural and human system models are also challenging. The data organization and the spatial and temporal scales are incompatible between natural and socioeconomic models. The representation of processes in ecohydrological models is typically distributed (grid, response unit, or network-node); however, in socioeconomic models and decision-making processes, this representation is lumped (political or administrative boundaries). Moreover, the natural system has relatively fast processes, whereas the human system is a slow process, and the evolution of values and norms can take tens to hundreds of years. Therefore, "socializing the pixel" (to aggregate gridded data to match the boundary of administrative units) and "pixelizing society" (to transform socioeconomic data into gridded data) are also becoming popular for developing a coevolved human-nature model (NRC, 1998). Multiscale coupling also brings uncertainty (Cai, 2008); therefore, a seamless structure or upscaling and downscaling of information to match the scale of other components is of critical importance.

4.2. Building a Scientific-Model-Based DSS

Integrated river basin management should be scientifically sound; thus, models used in DSS should have sufficient scientific support (Cai et al., 2015). However, decision support, involving the simulation and optimization procedures based on an integrated model with heterogeneous numerical representation, typically imposes a prohibitive computational burden, especially if uncertainties in different aspects of the model are also included. Therefore, to alleviate the computational burden, many DSSs are built using a simplified model (Ge et al., 2013), which is usually developed by referencing a scientific model with the aid of a model reduction technique.

One approach is to develop a simplified physically based model, in which the physical structure of the original model is simplified, the number of variables is reduced, and the spatial and temporal resolution are coarsened. These tasks required a huge amount of work. Additionally, when the original model, particularly its physical structure, is updated, the simplified model has to be updated as well. The simplified model built by this approach is called a lower-fidelity surrogate, which is a physically based but less detailed model.

Another approach is metamodeling, which is used to simplify the model from an information science perspective. This method can be applied to build a high-fidelity surrogate model using machine-learning methods, such as artificial neural networks, splines, and support vector machines. Additional numerical procedures for model reduction include proper orthogonal decomposition for partial differential equations and computational singular perturbation for stiff ordinary differential equations. In random space, Karhunen-Loeve expansion for stochastic processes and spectral surrogate models (Ghanem & Spanos, 2003; Marzouk, Najm, & Rahn, 2007; Xiu & Karniadakis, 2003) can reduce the dimensionality of the random space. This type of surrogate model is usually capable of minimizing the computational cost while maximizing the model accuracy (Gorissen et al., 2010). Generally, 80–97% of the CPU time can be saved in water resource applications (Razavi et al., 2012). Therefore, by developing a surrogate model, integrating computationally intensive tools, such as parameter estimation, scenario-based simulation, optimization, data assimilation, and ensemble prediction, into a DSS is feasible for making the DSS a pragmatic tool.

Another challenge of building a DSS is effectively making use of unstructured soft data. A soft system methodology is proposed to realize a qualitative-quantitative metasynthesis. For instance, a next-generation DSS could be a "Hall for Workshop on Meta-Synthetic Engineering" (Gu & Tang, 2005; Tang, 2007), which is a virtual environment that contains computer-aided human-human and human-computer interactions that are recursively used to synthesize both the qualitative opinions of stakeholders, scientists, and decision makers and the quantitative data from models.

4.3. Taking Advantage of Technique Progress

Progress in modeling lags behind the advances in observation and data techniques. Developing an integrated model must take advantage of the progress in Earth observation and cyberinfrastructure. Our vision of a watershed cyberinfrastructure is illustrated in Figure 5. In this framework, the model has good accessibility to, and integration with, the data system, sensor web, modeling environment, high-performance computation, and scientific visualization. We highlight two key technologies that next-generation models should take advantage of.

The first technology is big data. Deluging data and advances in data mining, machine learning, and artificial intelligence have enabled data-driven modeling of the complex human-nature system. Data-driven modeling in the big data era is different from traditional data-driven modeling because unstructured data, such as opinions from different stakeholders and values and norms of different societies, can now be efficiently and massively collected, normalized, and quantified using opinion mining and sentimental analysis (for example, Wei et al., 2017; Xiong et al., 2016). Additionally, big data technology not only plays a role in data acquisition, storage, and analytics but also is used in an unprecedented way to simulate and predict the evolution of social systems (King, 2011; Vespignani, 2009). We believe that next-generation models can combine data-driven and physically based approaches to model the complex human-nature system.

The second technology is virtual reality. Virtual reality and its updated technologies, such as augmented reality, enable people to handle, sense, interact, and visualize simulation results of geoscientific models (Lin et al., 2015). Particularly, a virtual geographic environment (VGE) can play a key role. A VGE is designed to support various types of geosimulations; near-real scientific visualization and public participation

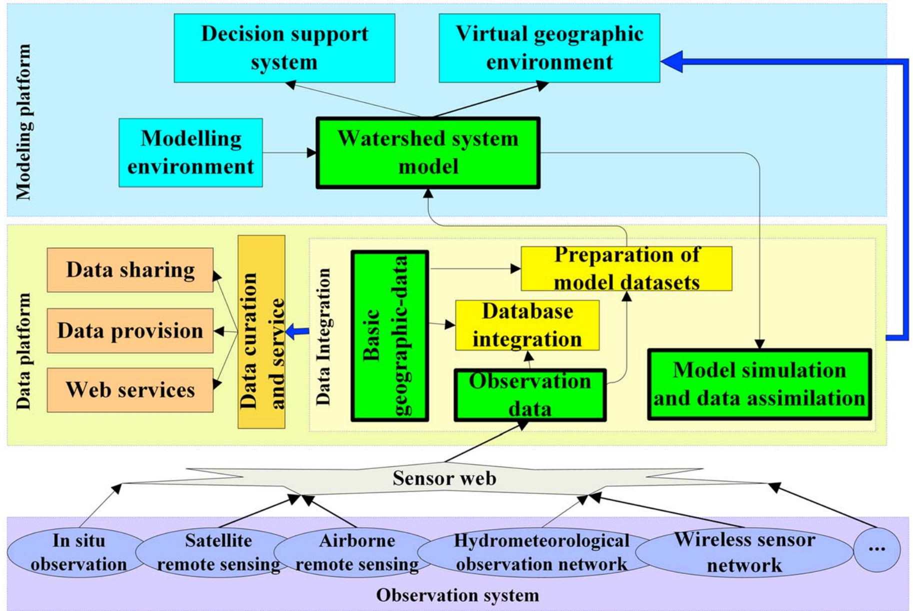

Figure 5. Watershed system model and the watershed cyberinfrastructure.

features are key properties of next-generation cyberinfrastructure. For scientists, a VGE is a virtual experimental platform, in which the interaction with models and volume visualization can provide new insights; for the public, a VGE is an immersive space to sense the watershed and participate in watershed decision making (Lin, Chen, & Lu, 2013; Lin, Chen, Lu, Zhu, et al., 2013). Therefore, we believe that VGEs are powerful tools to enable a digital watershed that can be virtually handled and visualized and help in the decision-making process.

4.4. Quantifying and Controlling Uncertainties

The complexity of a model increases with the number of modules/models to be integrated. In general, both the complexity of model physics and the number of parameters and model state variables increase accordingly. Therefore, quantifying and controlling uncertainties in such a high-dimensional and nonlinear model space poses a grand challenge (Beven & Freer, 2001). The current trend is to develop uncertainty estimations and controlling functions as an essential component in the model system or even as part of the model formulation (Li, 2014; Smith et al., 2014). Developers of integrated models should not act as “integronsters” (Voinov & Shugart, 2013) but rather as practitioners to create more applicable models by considering uncertainty estimation at the forefront of model integration. Without the embedded ability to estimate and control uncertainty, the applicability of the model would be highly questionable.

The state-of-the-science methods for uncertainty estimation and control include the following:

1. Global sensitivity analysis, which screens and ranks model parameters by quantifying their contributions to the total model error (e.g., Gan et al., 2014; Ma et al., 2017; Wang et al., 2013; Wu et al., 2014);
2. High-dimensional parameter calibration to achieve an unbiased prediction (Rouholahnejad et al., 2012);
3. Data assimilation, which is a generalized methodology to reduce and control uncertainty via model-data fusion (e.g., Lei et al., 2014; Li, 2014); and
4. Ensemble prediction, a postprocessing approach to reduce model error using a single model ensemble or multimodel ensemble by general or Bayesian model averaging (Cloke & Pappenberger, 2009; Duan et al., 2007).

Furthermore, communicating uncertainties to decision makers is important. The quantification of uncertainties and propagation to risk analysis at the decision maker level not only increases the predictability of the model but also helps inform decision makers (Weaver et al., 2013).

4.5. Embracing Macro Science

True advances in integrated watershed modeling are based on scientific advances. Watershed science itself is a transformative science. Breakthroughs occur in the interdisciplinary areas of hydrology, ecology, and sustainability science. New ideas, such as using statistical mechanics in simulating complex systems, upscaling by ensemble averaging, Darwinian evolutionary computation, and soft systems methodology and other metasynthesis methods, are reshaping watershed science (Cheng & Li, 2015). Integrated watershed modeling should embrace these advancements.

5. Prospects of New-Generation Watershed System Models

Integrated watershed modeling is increasingly important as a vehicle for exploring complex watershed systems and as a tool for integrated river basin management. We argue that integrated watershed modeling will serve for both scientific understanding and watershed management practices. The watershed system model should represent the processes and coevolution of the water-land-air-plant-human nexus in a watershed. The management-oriented model is a surrogate of watershed system models that are equipped with decision-making algorithms.

We propose that the model structure can be decomposed into the physical structure, input and output interfaces, user interface, and auxiliary tools. Model integration can be implemented with the know-how approach, through which the various components are integrated into a new, consistent model, or with the technical approach, through which the various models are coupled through data exchange interfaces. We highlight that a modeling environment is a very useful tool to facilitate effective model integration. We propose a method of building a scientifically sound DSS through metamodeling and predefined scenarios.

We argue that the development of a watershed system model is not only a software engineering problem but also a know-how synthesis. This development faces the grand challenges of modeling the human system and its interaction with the natural system using unstructured soft data and agent-based modeling, building scientific model-based DSS, taking advantage of new techniques, (e.g., big data and virtual reality), quantifying and controlling uncertainties, scaling to the watershed scale, and benefiting from other transformative thinking on watershed science. Integrated modeling should coevolve with the advancements in watershed science.

We suggest that methodology to build the next-generation watershed system models should feature the following tasks:

Bridging Newtonian and Darwinian approaches. The integration of a natural system model will be realized through a synthesis by examining a watershed from the different perspectives in hydrology and ecology (Harte, 2002). A macroscale model (Dooge, 1986; Sivapalan, 2005) would be possible by introducing macroscale laws and simulating the evolution of the self-organized complex watershed system using both Newtonian dynamics and evolutionary dynamics advocated by the Darwinian world view.

Visioneering soft systems methodology. Human system dynamics will be fully simulated and coupled with the natural system model. Soft system methodologies would become increasingly important because they can represent unstructured issues. Big data and machine-learning technologies would enable the merging of various types of soft data, which is critical in characterizing the human system. The synthesis of quantitative and qualitative analyses via recursive human-machine interactions and computer-aided human-human interactions would make the human-nature system more predictable and "smart" river basins possible (Jiang, Ye, & Wang, 2011).

Uncertainty reduction by merging multisource or crowdsource data into the modeling procedures via data assimilation. Deluging Earth observation data are expected to be successfully used to constrain the high-dimensional, stochastic, overly complex watershed system model. Model-data fusion methods, such as data assimilation and high-dimensional parameter estimation, would be essential components of the modeling system.

Codesigning and coproduction. The previous three critical issues in model integration cannot be achieved by individuals. Watershed system models require community development. Methods will be developed to ensure creative teamwork. Artificial intelligence would also be involved in the codesign and coproduction processes.

In summary, our goal is to build a transdisciplinary, scientifically sound, scale-explicit, and falsifiable watershed system model codesigned by multiple communities. This will benefit the Earth-surface system science research and integrated river basin management.

Acknowledgments
This work is supported by the National Natural Science Foundation of China (grants 91425303 and 41630856) and the National Key Basic Research Program of China (2015CB954103). We thank Dawen Yang, Chunmiao Zheng, Xiangzheng Deng, Junguo Liu, and Xujun Han for their valuable comments. All the data related to this work are available at the data center of the "Integrated research on the eco-hydrological process of the Heihe River basin" (http://www.heihedata.org) and the World Data System Cold and Arid Regions Science Data Center (http://card.westgis.ac.cn).

References

Adam, J. C., Stephens, J. C., Chung, S. H., Barady, M. P., Evans, R. D., Kruger, C. E., et al. (2014). BioEarth: Envisioning and developing a new regional Earth system model to inform natural and agricultural resource management. *Climatic Change*, *129*(3–4), 555–571.

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*, *229*, 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010

Argent, R. M. (2004). An overview of model integration for environmental application—Components, frameworks and semantics. *Environmental Modelling and Software*, *19*(3), 219–234. https://doi.org/10.1016/S1364-8152(03)00150-6

Argent, R. M., Perraud, J. M., Rahman, J. M., Grayson, R. B., & Podger, G. M. (2009). A new approach to water quality modelling and environmental decision support systems. *Environmental Modelling and Software*, *24*(7), 809–818. https://doi.org/10.1016/j.envsoft.2008.12.010

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

Beven, K., & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology*, *249*, 11–29.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(Supplement 3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Boumans, R., Roman, J., Altman, I., & Kaufman, L. (2015). The Multiscale Integrated Model of Ecosystem Services (MIMES): Simulating the interactions of coupled human and natural systems. *Ecosystem Services*, *12*, 30–41. https://doi.org/10.1016/j.ecoser.2015.01.004

Bousquet, F., & Le Page, C. (2004). Multi-agent simulations and ecosystem management: A review. *Ecological Modelling*, *176*(3-4), 313–332. https://doi.org/10.1016/j.ecolmodel.2004.01.011

Brunner, P., & Simmons, C. T. (2012). HydroGeoSphere: A fully integrated, physically based hydrological model. *Groundwater*, *50*(2), 170–176. https://doi.org/10.1111/j.1745-6584.2011.00882.x

Cai, X. M. (2008). Implementation of holistic water resources-economic optimization models for river basin management—Reflective experiences. *Environmental Modelling and Software*, *23*(1), 2–18. https://doi.org/10.1016/j.envsoft.2007.03.005

Cai, X. M., Marston, L., & Ge, Y. C. (2015). Decision support for integrated river basin management—Scientific research challenges. *Science China Earth Sciences*, *58*(1), 16–24. https://doi.org/10.1007/s11430-014-5005-2

Cai, X. M., McKinney, D. C., & Lasdon, L. S. (2003). Integrated hydrologic-agronomic-economic model for river basin management. *Journal of Water Resources Planning and Management: American Society of Civil Engineers*, *129*(1), 4–17. https://doi.org/10.1061/(ASCE)0733-9496(2003)129:1(4)

Castronova, A. M., & Goodall, J. L. (2013). Simulating watersheds using loosely integrated model components: Evaluation of computational scaling using OpenMI. *Environmental Modelling and Software*, *39*, 304–313. https://doi.org/10.1016/j.envsoft.2012.01.020

Castronova, A. M., Goodall, J. L., & Ercan, M. B. (2013). Integrated modeling within a hydrologic information system: An OpenMI based approach. *Environmental Modelling and Software*, *39*, 263–273. https://doi.org/10.1016/j.envsoft.2012.02.011

Chen, M., Tao, H., Lin, H., & Wen, Y. N. (2011). A visualization method for geographic conceptual modelling. *Annals of GIS*, *17*(1), 15–29. https://doi.org/10.1080/19475683.2011.558024

Cheng, G. D. (2009). *Integrated management of the water-ecology-economy system in the Heihe River basin* (in Chinese) (581 pp.). Beijing: Sci. Press.

Cheng, G. D., & Li, X. (2015). Integrated research methods in watershed science. *Science China Earth Sciences*, *58*(7), 1159–1168. https://doi.org/10.1007/s11430-015-5074-x

Cheng, G. D., Li, X., Zhao, W. Z., Xu, Z. M., Feng, Q., Xiao, S. C., & Xiao, H. L. (2014). Integrated study of the water-ecosystem-economy in the Heihe River basin. *National Science Review*, *1*(3), 413–428. https://doi.org/10.1093/nsr/nwu017

Cloke, H. L., & Pappenberger, F. (2009). Ensemble flood forecasting: A review. *Journal of Hydrology*, *375*(3-4), 613–626. https://doi.org/10.1016/j.jhydrol.2009.06.005

Consortium of Universities for the Advancement of Hydrologic Science (CUAHSI) (2007). *Hydrology of a dynamic Earth: A decadal research plan for hydrologic science*. USA: CUAHSI Science Plan.

David, O., Ascough, J. C. II, Lloyd, W., Green, T. R., Rojas, K. W., Leavesley, G. H., & Ahuja, L. R. (2013). A software engineering perspective on environmental modeling framework design: The object modeling system. *Environmental Modelling and Software*, *39*, 201–213. https://doi.org/10.1016/j.envsoft.2012.03.006

DHI (2003). MIKE BASIN 2003, A versatile decision support tool for integrated water resources management planning.

Dolk, D. R. (1993). An introduction to model integration and integrated modeling environments. *Decision Support Systems*, *10*(3), 249–254. https://doi.org/10.1016/0167-9236(93)90062-8

Dolk, D. R., & Kottemann, J. E. (1993). Model integration and a theory of models. *Decision Support Systems*, *9*(1), 51–63. https://doi.org/10.1016/0167-9236(93)90022-U

Dooge, J. C. I. (1986). Looking for hydrologic laws. *Water Resources Research*, *22*(9S), 46S–58S. https://doi.org/10.1029/WR022i09Sp0046S

Duan, Q., Ajami, N. K., Gao, X., & Sorooshian, S. (2007). Multi-model ensemble hydrologic prediction using Bayesian model averaging. *Advances in Water Resources*, *30*(5), 1371–1386. https://doi.org/10.1016/j.advwatres.2006.11.014

EPA (2001). *Better assessment science integrating point and nonpoint sources: Basins version 3.0*. Washington, DC: EPA.

Gan, Y. J., Duan, Q. Y., Gong, W., Tong, C., Sun, Y. W., Chu, W., et al. (2014). A comprehensive evaluation of various sensitivity analysis methods: A case study with a hydrological model. *Environmental Modelling and Software*, *51*, 269–285. https://doi.org/10.1016/j.envsoft.2013.09.031

Gao, B., Qin, Y., Wang, Y. H., Yang, D. W., & Zheng, Y. R. (2016). Modeling ecohydrological processes and spatial patterns in the upper Heihe basin in China. *Forests*, *7*(1), 10.

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. https://doi.org/10.13031/2013.23637

Ge, Y. C., Li, X., Huang, C. L., & Nan, Z. T. (2013). A decision support system for irrigation water allocation along the middle reaches of the Heihe River basin, northwest China. *Environmental Modelling and Software*, *47*, 182–192. https://doi.org/10.1016/j.envsoft.2013.05.010

Ghanem, R. G., & Spanos, P. D. (2003). *Stochastic finite elements: A spectral approach*. North Chelmsford: Courier Corporation.
Gorissen, D., Couckuyt, I., Demeester, P., Dhaene, T., & Crombecq, K. (2010). A surrogate modeling and adaptive sampling toolbox for computer based design. *Journal of Machine Learning Research*, *11*, 2051–2055.
Graham, D. N., & Butts, M. B. (2005). Flexible, integrated watershed modelling with MIKE SHE. In V. P. Singh & D. K. Frevert (Eds.), *Watershed models* (pp. 245–272). Boca Raton, FL: CRC Press.
Granell, C., Schade, S., & Ostländer, N. (2013). Seeing the forest through the trees: A review of integrated environmental modelling tools. *Computers, Environment and Urban Systems*, *41*, 136–150. https://doi.org/10.1016/j.compenvurbsys.2013.06.001
Gregersen, J., Gijsbers, P., & Westen, S. (2007). OpenMI: Open modelling interface. *Journal of Hydroinformatics*, *9*(3), 175–191. https://doi.org/10.2166/hydro.2007.023
Gu, J., & Tang, X. (2005). Meta-synthesis approach to complex system modeling. *European Journal of Operational Research*, *166*(3), 597–614. https://doi.org/10.1016/j.ejor.2004.03.036
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. *Journal of Hydrology*, *375*(3-4), 627–643. https://doi.org/10.1016/j.jhydrol.2009.06.037
Harte, J. (2002). Toward a synthesis of the Newtonian and Darwinian worldviews. *Physics Today*, *55*(10), 29–34. https://doi.org/10.1063/1.1522164
Hill, C., DeLuca, C., Suarez, M., & da Silva, A. (2004). The architecture of the Earth system modeling framework. *Computing in Science & Engineering*, *6*(1), 18–28. https://doi.org/10.1109/MCISE.2004.1255817
Hu, Y., Cai, X. M., & DuPont, B. (2015). Design of a web-based application of the coupled multi-agent system model and environmental model for watershed management analysis using Hadoop. *Environmental Modelling and Software*, *70*, 149–162. https://doi.org/10.1016/j.envsoft.2015.04.011
Jiang, Y. Z., Ye, Y. T., & Wang, H. (2011). Smart basin and its prospects for application [in Chinese with English abstract]. *Systems Engineering - Theory & Practice*, *31*(6), 1174–1181.
Jöckel, P., Sander, R., Kerkweg, A., Tost, H., & Lelieveld, J. (2005). Technical note: The modular Earth submodel system (MESSY)—A new approach towards Earth system modeling. *Atmospheric Chemistry and Physics*, *5*(2), 433–444. https://doi.org/10.5194/acp-5-433-2005
Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., et al. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling and Software*, *47*, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005
King, G. (2011). Ensuring the data-rich future of the social sciences. *Science*, *331*(6018), 719–721. https://doi.org/10.1126/science.1197872
Knapen, R., Janssen, S., Roosenschoon, O., Verweij, P., De Winter, W., Uiterwijk, M., & Wien, J. E. (2013). Evaluating OpenMI as a model integration platform across disciplines. *Environmental Modelling and Software*, *39*, 274–282. https://doi.org/10.1016/j.envsoft.2012.06.011
Kollet, S. J., & Maxwell, R. M. (2006). Integrated surface-groundwater flow modeling: A free-surface overland flow boundary condition in a parallel groundwater flow model. *Advances in Water Resources*, *29*(7), 945–958. https://doi.org/10.1016/j.advwatres.2005.08.006
Kumar, S. V., Peters-Lidard, C. D., Tian, Y., Houser, P. R., Geiger, J., Olden, S., et al. (2006). Land information system: An interoperable framework for high resolution land surface modeling. *Environmental Modelling and Software*, *21*(10), 1402–1415. https://doi.org/10.1016/j.envsoft.2005.07.004
Laniak, G. F., Olchin, G., Goodall, J., Voinov, A., Hill, M., Glynn, P., et al. (2013). Integrated environmental modeling: A vision and roadmap for the future. *Environmental Modelling and Software*, *39*, 3–23. https://doi.org/10.1016/j.envsoft.2012.09.006
Larsen, M. A. D., Refsgaard, J. C., Drews, M., Butts, M. B., Jensen, K. H., Christensen, J. H., & Christensen, O. B. (2014). Results from a full coupling of the HIRHAM regional climate model and the MIKE SHE hydrological model for a Danish catchment. *Hydrology and Earth System Sciences*, *18*(11), 4733–4749. https://doi.org/10.5194/hess-18-4733-2014
Leavesley, G. H., Restrepo, P. J., Markstrom, S. L., Dixon, M., & Stannard, L. G. (1996). The modular modeling system (MMS)—User's manual, U.S. Geological Survey Open-File Report, 96-151.
Lei, F. N., Huang, C. L., Shen, H. F., & Li, X. (2014). Improving the estimation of hydrological states in SWAT model via the ensemble Kalman smoother: Synthetic experiments for the Heihe basin in northwest China. *Advances in Water Resources*, *67*, 32–45. https://doi.org/10.1016/j.advwatres.2014.02.008
Li, X. (2014). Characterization, controlling and reduction of uncertainties in the modeling and observation of land-surface systems. *Science China Earth Sciences*, *57*(1), 80–87. https://doi.org/10.1007/s11430-013-4728-9
Li, X., Cheng, G. D., Ge, Y. C., Li, H. Y., Han, F., Hu, X. L., et al. (2018). Hydrological cycle in the Heihe River basin and its implication for water resource management in endorheic basins. *Journal of Geophysical Research: Atmospheres*, *123*, 890–914. https://doi.org/10.1002/2017JD027889
Li, X., Cheng, G. D., Kang, E. S., Xu, Z. M., Nan, Z. T., Zhou, J., et al. (2010). Digital Heihe River basin. 3: Model integration. *Advances in Earth Science*, *25*(8), 851–865.
Li, X., Cheng, G. D., Liu, S. M., Xiao, Q., Ma, M. G., Jin, R., et al. (2013). Heihe Watershed Allied Telemetry Experimental Research (HiWATER): Scientific objectives and experimental design. *Bulletin of the American Meteorological Society*, *94*(8), 1145–1160. https://doi.org/10.1175/BAMS-D-12-00154.1
Li, X., Wu, L. Z., Ma, M. G., Ge, Y. C., Ran, Y. H., Wang, L. X., & Nan, Z. T. (2010). Digital Heihe River basin. 2: Data integration (in Chinese). *Advances in Earth Science*, *25*(3), 306–316.
Li, Y., Zhou, J., Kinzelbach, W., Cheng, G. D., Li, X., & Zhao, W. Z. (2013). Coupling a SVAT heat and water flow model, a stomatal-photosynthesis model and a crop growth model to simulate energy, water and carbon fluxes in an irrigated maize ecosystem. *Agricultural and Forest Meteorology*, *176*, 10–24. https://doi.org/10.1016/j.agrformet.2013.03.004
Lin, H., Batty, M., Jørgensen, S. E., Fu, B., Konecny, M., Voinov, A., et al. (2015). Virtual environments begin to embrace process-based geographic analysis. *Transactions in GIS*, *19*(4), 493–498. https://doi.org/10.1111/tgis.12167
Lin, H., Chen, M., & Lu, G. (2013). Virtual geographic environment: A workspace for computer-aided geographic experiments. *Annals of the Association of American Geographers*, *103*(3), 465–482. https://doi.org/10.1080/00045608.2012.689234
Lin, H., Chen, M., Lu, G. N., Zhu, Q., Gong, J. H., You, X., et al. (2013). Virtual geographic environments (VGEs): A new generation of geographic analysis tool. *Earth Science Reviews*, *126*, 74–84. https://doi.org/10.1016/j.earscirev.2013.08.001
Ma, C. F., Li, X., Wang, J., Wang, C., Duan, Q. Y., & Wang, W. Z. (2017). A comprehensive evaluation of microwave emissivity and brightness temperature sensitivities to soil parameters using qualitative and quantitative sensitivity analyses. *IEEE Transactions on Geoscience and Remote*, *55*(2), 1025–1038. https://doi.org/10.1109/TGRS.2016.2618903
Markstrom, S. L., Niswonger, R. G., Regan, R. S., Prudic, D. E., & Barlow, P. M. (2008). GSFLOW—Coupled Ground-water and Surface-water FLOW model based on the integration of the Precipitation-Runoff Modeling System (PRMS) and the Modular Ground-Water Flow Model (MODFLOW-2005), U.S. Geol. Surv. Tech. Methods, 6-d1.

Marzouk, Y. M., Najm, H. N., & Rahn, L. A. (2007). Stochastic spectral methods for efficient Bayesian solution of inverse problems. *Journal of Computational Physics*, *224*(2), 560–586. https://doi.org/10.1016/j.jcp.2006.10.010

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: A review of applications. *Landscape Ecology*, *22*(10), 1447–1459. https://doi.org/10.1007/s10980-007-9135-1

Maxwell, T., & Costanza, R. (1997). An open geographic modeling environment. *Simulation*, *68*(3), 175–185.

McKinney, D. C., Cai, X. M., Rosegrant, W. W., Ringler, C., & Scott, C. A. (1999). Modeling water resources management at the basin level: Review and future directions. In *System-wide initiative on water management*. SWIM Paper 6. Colombo, Sri Lanka: Int. Water Manage. Inst.

Mirchi, A., Watkins, D. Jr., & Madani, K. (2010). Modeling for watershed planning, management, and decision making. In *Watersheds: Management, restoration, and environmental impact* (Chap. 6). New York: Nova Sci. Publishers.

Monticino, M., Acevedo, M., Callicott, B., Cogdill, T., & Lindquist, C. (2007). Coupled human and natural systems: A multi-agent-based approach. *Environmental Modelling and Software*, *22*(5), 656–663. https://doi.org/10.1016/j.envsoft.2005.12.017

Nazemi, A., & Wheater, H. S. (2015a). On inclusion of water resource management in Earth system models—Part 2: Representation of water supply and allocation and opportunities for improved modeling. *Hydrology and Earth System Sciences*, *19*(1), 63–90. https://doi.org/10.5194/hess-19-63-2015

Nazemi, A., & Wheater, H. S. (2015b). On inclusion of water resource management in Earth system models—Part 1: Problem definition and representation of water demand. *Hydrology and Earth System Sciences*, *19*(1), 33–61.

Ng, T. L., Eheart, J. W., Cai, X., & Braden, J. B. (2011). An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop. *Water Resources Research*, *47*, W09519. https://doi.org/10.1029/2011WR010399

Niu, G. Y., Paniconi, C., Troch, P. A., Scott, R. L., Durcik, M., Zeng, X. B., et al. (2014). An integrated modelling framework of catchment-scale ecohydrological processes: 1. Model description and tests over an energy-limited watershed. *Ecohydrology*, *7*(2), 427–439. https://doi.org/10.1002/eco.1362

NRC, Committee on the Human Dimensions of Global Change (1998). *People and pixels: Linking remote sensing and social science* (p. 256). Washington, DC: National Academies Press.

Price, A., Lenton, T., Cox, C., Valdes, P., & Shepherd, J. (2005). GENIE: Grid Enabled Integrated Earth System Model. *ERCIM News*, *61*, 15–16.

Qin, Y., Lei, H. M., Yang, D. W., Gao, B., Wang, Y. H., Cong, Z. T., & Fan, W. J. (2016). Long-term change in the depth of seasonally frozen ground and its ecohydrological impacts in the Qilian Mountains, northeastern Tibetan Plateau. *Journal of Hydrology*, *542*, 204–221. https://doi.org/10.1016/j.jhydrol.2016.09.008

Ray, D. K., Pijanowski, B. C., Kendall, A. D., & Hyndman, D. W. (2012). Coupling land use and groundwater models to map land use legacies: Assessment of model uncertainties relevant to land use planning. *Applied Geography*, *34*, 356–370. https://doi.org/10.1016/j.apgeog.2012.01.002

Razavi, S., Tolson, B. A., & Burn, D. H. (2012). Review of surrogate modeling in water resources. *Water Resources Research*, *48*, W07401. https://doi.org/10.1029/2011WR011527

Reid, W. V., Chen, D., Goldfard, L., Hackmann, H., Lee, Y. T., Mokhele, K., et al. (2010). Earth system science for global sustainability: Grand challenges. *Science*, *330*(6006), 916–917. https://doi.org/10.1126/science.1196263

Rouholahnejad, E., Abbaspour, K. C., Vejdani, M., Srinivasan, R., Schulin, R., & Lehmann, A. (2012). A parallelization framework for calibration of hydrological models. *Environmental Modelling and Software*, *31*, 28–36. https://doi.org/10.1016/j.envsoft.2011.12.001

Savenije, H. H. G. (2009). HESS opinions "The art of hydrology". *Hydrology and Earth System Sciences*, *13*(2), 157–161. https://doi.org/10.5194/hess-13-157-2009

Schellnhuber, H. J. (1999). 'Earth system' analysis and the second Copernican revolution. *Nature*, *402*(SUPP), C19–C23.

Sivapalan, M. (2005). Pattern, process and function: Elements of a unified theory of hydrology at the catchment scale. In M. G. Anderson (Ed.), *Encyclopedia of hydrological sciences* (pp. 193–220). Hoboken, NJ: John Wiley. https://doi.org/10.1002/0470848944.hsa012

Sivapalan, M., Konar, M., Srinivasan, V., Chhatre, A., Wutich, A., Scott, C. A., et al. (2014). Socio-hydrology: Use-inspired water sustainability science for the Anthropocene. *Earth's Future*, *2*(4), 225–230. https://doi.org/10.1002/2013EF000164

Sivapalan, M., Savenije, H. H., & Blöschl, G. (2012). Socio-hydrology: A new science of people and water. *Hydrological Processes*, *26*(8), 1270–1276. https://doi.org/10.1002/hyp.8426

Smajgl, A., Brown, D. G., Valbuena, D., & Huigen, M. G. (2011). Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling and Software*, *26*(7), 837–844. https://doi.org/10.1016/j.envsoft.2011.02.011

Smith, M. J., Palmer, P. I., Purves, D. W., Vanderwel, M. C., Lyutsarev, V., Calderhead, B., et al. (2014). Changing how Earth system modelling is done to provide more useful information for decision making, science, and society. *Bulletin of the American Meteorological Society*, *95*(9), 1453–1464. https://doi.org/10.1175/BAMS-D-13-00080.1

Surridge, B., & Harris, B. (2007). Science-driven integrated river basin management: A mirage? *Interdisciplinary Science Reviews*, *32*(3), 298–312. https://doi.org/10.1179/030801807X211711

Tang, X. (2007). Towards meta-synthetic support to unstructured problem solving. *International Journal of Information Technology and Decision*, *06*(03), 491–508. https://doi.org/10.1142/S0219622007002630

Tang, X. J. (2001). Model integration (in Chinese). *Journal of Systems Engineering*, *16*(5), 322–329.

Tian, S., Youssef, M. A., Skaggs, R. W., Amatya, D. M., & Chescheir, G. M. (2012). DRAINMOD-FOREST: Integrated modeling of hydrology, soil carbon and nitrogen dynamics, and plant growth for drained forests. *Journal of Environmental Quality*, *41*(3), 764–782. https://doi.org/10.2134/jeq2011.0388

Tian, Y., Zheng, Y., Wu, B., Wu, X., Liu, J., & Zheng, C. (2015). Modeling surface water-groundwater interaction in arid and semi-arid regions with intensive agriculture. *Environmental Modelling and Software*, *63*, 170–184. https://doi.org/10.1016/j.envsoft.2014.10.011

Tian, Y., Zheng, Y., Zheng, C., Xiao, H., Fan, W., Zou, S., et al. (2015). Exploring scale-dependent ecohydrological responses in a large endorheic river basin through integrated surface water-groundwater modeling. *Water Resources Research*, *51*, 4065–4085. https://doi.org/10.1002/2015WR016881

Valcke, S. (2013). The OASIS3 coupler: A European climate modelling community software. *Geoscientific Model Development*, *6*(2), 373–388. https://doi.org/10.5194/gmd-6-373-2013

Valcke, S., Craig, A., Dunlap, R., & Riley, G. D. (2016). Sharing experiences and outlook on coupling technologies for Earth system models. *Bulletin of the American Meteorological Society*, *97*(3), ES53–ES56. https://doi.org/10.1175/BAMS-D-15-00239.1

Vespignani, A. (2009). Predicting the behavior of techno-social systems. *Science*, *325*(5939), 425–428. https://doi.org/10.1126/science.1171990

Vogel, R. M., Lall, U., Cai, X. M., Rajagopalan, B., Weiskel, P. K., Hooper, R. P., & Matalas, N. C. (2015). Hydrology: The interdisciplinary science of water. *Water Resources Research*, *51*, 4409–4430. https://doi.org/10.1002/2015WR017049

Voinov, A., Costanza, R., Wainger, L., Boumans, R., Villa, F., Maxwell, T., & Voinov, H. (1999). Patuxent landscape model: Integrated ecological economic modeling of a watershed. *Environmental Modelling and Software*, *14*(5), 473–491. https://doi.org/10.1016/S1364-8152(98)00092-9

Voinov, A., & Shugart, H. H. (2013). 'Integronsters', integral and integrated modeling. *Environmental Modelling and Software*, *39*, 149–158. https://doi.org/10.1016/j.envsoft.2012.05.014

Wagner, S., Fersch, B., Yuan, F., Yu, Z., & Kunstmann, H. (2016). Fully coupled atmospheric-hydrological modeling at regional and long-term scales: Development, application, and analysis of WRF-HMS. *Water Resources Research*, *52*, 3187–3211. https://doi.org/10.1002/2015WR018185

Wang, J., Li, X., Lu, L., & Fang, F. (2013). Parameter sensitivity analysis of crop growth model based on the extended Fourier amplitude sensitivity test method. *Environmental Modelling and Software*, *48*, 171–182. https://doi.org/10.1016/j.envsoft.2013.06.007

Wang, L., Koike, T., Yang, K., Jin, R., & Li, H. (2010). Frozen soil parameterization in a distributed biosphere hydrological model. *Hydrology and Earth System Sciences*, *14*(3), 557–571. https://doi.org/10.5194/hess-14-557-2010

Wang, X. S. (2007). *Three-dimensional finite difference model based on the aquifer-flow of saturated groundwater flow* (in Chinese). Beijing: China University of Geosci.

Wang, X. S., Ma, M. G., Li, X., Zhao, J., Dong, P., & Zhou, J. (2010). Groundwater response to leakage of surface water through a thick vadose zone in the middle reaches area of Heihe River basin, in China. *Hydrology and Earth System Sciences*, *14*(4), 639–650. https://doi.org/10.5194/hess-14-639-2010

Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., & Sarewitz, D. (2013). Improving the contribution of climate model information to decision making: The value and demands of robust decision frameworks. *WIREs Climate Change*, *4*(1), 39–60. https://doi.org/10.1002/wcc.202

Wei, J., Wei, Y., & Western, A. (2017). Evolution of the societal value of water resources for economic development versus environmental sustainability in Australia from 1843 to 2011. *Global Environmental Change*, *42*(Supplement C), 82–92. https://doi.org/10.1016/j.gloenvcha.2016.12.005

Wen, Y. N., Chen, M., Lu, G. N., Lin, H., He, L., & Yue, S. S. (2013). Prototyping an open environment for sharing geographical analysis models on cloud computing platform. *International Journal of Digital Earth*, *6*(4), 356–382. https://doi.org/10.1080/17538947.2012.716861

Wu, B., Zheng, Y., Tian, Y., Wu, X., Yao, Y., Han, F., et al. (2014). Systematic assessment of the uncertainty in integrated surface water-groundwater modeling based on the probabilistic collocation method. *Water Resources Research*, *50*, 554–563. https://doi.org/10.1002/2014WR015366

Wu, B., Zheng, Y., Wu, X., Tian, Y., Han, F., Liu, J., & Zheng, C. (2015). Optimizing water resources management in large river basins with integrated surface water-groundwater modeling: A surrogate-based approach. *Water Resources Research*, *51*, 2153–2173. https://doi.org/10.1002/2014WR016653

Wu, X., Zheng, Y., Wu, B., Tian, Y., Han, F., & Zheng, C. (2016). Optimizing conjunctive use of surface water and groundwater for irrigation to address human-nature water conflicts: A surrogate modeling approach. *Agricultural Water Management*, *163*, 380–392. https://doi.org/10.1016/j.agwat.2015.08.022

Xiong, Y., Wei, Y., Zhang, Z., & Wei, J. (2016). Evolution of China's water issues as framed in Chinese mainstream newspaper. *Ambio*, *45*(2), 241–253. https://doi.org/10.1007/s13280-015-0716-y

Xiu, D., & Karniadakis, G. E. (2003). Modeling uncertainty in flow simulations via generalized polynomial chaos. *Journal of Computational Physics*, *187*(1), 137–167. https://doi.org/10.1016/S0021-9991(03)00092-5

Yang, D. W., Gao, B., Yang, J., Lei, H. M., Zhang, Y. L., Yang, H. B., & Cong, Z. T. (2015). A distributed scheme developed for eco-hydrological modeling in the upper Heihe River. *Science China Earth Sciences*, *58*(1), 36–45. https://doi.org/10.1007/s11430-014-5029-7

Yang, Y. E., Zhao, J., & Cai, X. (2011). Decentralized optimization method for water allocation management in the Yellow River basin. *Journal of Water Resources Planning and Management: American Society of Civil Engineers*, *138*(4), 313–325.

Yao, Y. Y., Zheng, C. M., Tian, Y., Li, J., & Zheng, Y. (2015). Numerical modeling of regional groundwater flow in the Heihe River basin, China: Advances and new insights. *Science China Earth Sciences*, *58*(1), 3–15. https://doi.org/10.1007/s11430-014-5033-y

Zhang, Y. L., Chen, G. D., Li, X., Han, X. J., Wang, L., Li, H. Y., et al. (2013). Coupling of a simultaneous heat and water model with a distributed hydrological model and evaluation of the combined model in a cold region watershed. *Hydrological Processes*, *27*(25), 3762–3776. https://doi.org/10.1002/hyp.9514

Zhang, Y. L., Cheng, G. D., Li, X., Jin, H. J., Yang, D. W., Flerchinger, G. N., et al. (2017). Influences of frozen ground and climate change on the hydrological processes in an alpine watershed: A case study in the upstream area of the Hei'he River, northwest China. *Permafrost Periglac.*, *28*(2), 420–432. https://doi.org/10.1002/ppp.1928

Zhou, J., Pomeroy, J. W., Zhang, W., Cheng, G. D., Wang, G. X., & Chen, C. (2014). Simulating cold regions hydrological processes using a modular model in the west of China. *Journal of Hydrology*, *509*, 13–24. https://doi.org/10.1016/j.jhydrol.2013.11.013