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Global change and the groundwater management challenge

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Key Points:
- Six categories of groundwater vulnerability are central to future aquifer management
- Highly complex hydrologic-human interactions will require multiagent system models
- Aquifer management models have increasingly employed gradient-free optimization methods

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Abstract With rivers in critical regions already exploited to capacity throughout the world and groundwater overdraft as well as large-scale contamination occurring in many areas, we have entered an era in which multiple simultaneous stresses will drive water management. Increasingly, groundwater resources are taking a more prominent role in providing freshwater supplies. We discuss the competing fresh groundwater needs for human consumption, food production, energy, and the environment, as well as physical hazards, and conflicts due to transboundary overexploitation. During the past 50 years, groundwater management modeling has focused on combining simulation with optimization methods to inspect important problems ranging from contaminant remediation to agricultural irrigation management. The compound challenges now faced by water planners require a new generation of aquifer management models that address the broad impacts of global change on aquifer storage and depletion trajectory management, land subsidence, groundwater-dependent ecosystems, seawater intrusion, anthropogenic and geogenic contamination, supply vulnerability, and long-term sustainability. The scope of research efforts is only beginning to address complex interactions using multiagent system models that are not readily formulated as optimization problems and that consider a suite of human behavioral responses.

1. Introduction

Groundwater represents the largest stock of accessible freshwater and accounts for about one-third of freshwater withdrawals globally [*Siebert et al*., 2010; *Famiglietti*, 2014]. In 2010 in the U.S., groundwater provided 37% of the total public water supply and 98% of self-supplied freshwater [*Maupin et al*., 2014; also see *Alley et al*., 2002]. In the European Union as a whole, groundwater supplies 70% of domestic use. In India, the rate of groundwater abstraction has increased tenfold in the past 50 years, making it the nation with the greatest total groundwater production in 2010, with twice the annual abstraction of either the U.S. or China [*Margat and van der Gun*, 2013]. Mining of nonrenewable aquifers is currently critical in places like Jordan, where the majority of municipal water is supplied by groundwater.

Large aquifers that are negligibly recharged are being mined around the world. The Nubian aquifer extending into parts of Egypt, Chad, Libya, and Sudan, has experienced 60 m of drawdown in Egypt with a cone of depression entering into Sudan [*Puri and Aureli*, 2009; *Gleeson et al*., 2010]. Minimally recharged parts of the High Plains aquifer in Kansas and Texas have been mined since the 1940s and water levels have declined up to 50 m [*Konikow*, 2013]. Although essential to regional irrigated agricultural economies, continuing groundwater overexploitation in such regions is unsustainable over multiple generations. On one hand, the volumes of some aquifer systems are enormous. For example, the Nubian sandstone system in Libya contains an estimated 4850 km^3, while extraction was 0.9 km^3/yr in 2000, suggesting up to several hundreds or perhaps thousands of years of supply [*Margat and van der Gun*, 2013]. On the other hand, mining groundwater is analogous to mining a mineral resource. With increased extraction, the “grade” or relative richness of the resource declines. In the case of groundwater, as hydraulic heads drop, well depths and pumping lifts increase with a consequent rise in production costs, and in some cases water quality can diminish as less desirable deep groundwater is produced.

Groundwater exploitation and contamination have become global problems [*Gregory et al*., 2013; *Zheng and Liu*, 2013]. We are now experiencing distinct regional “tragedy of the commons” [*Hardin*, 1968] at a global scale in which individual aquifer users act to maximize their own benefits, but the shared aquifer resource suffers aggregate impacts with consequent costs to humans and the environment. Solutions to this dilemma include privatization, top down governmental regulations, and nonmarket bottom up resource sharing by communities that benefit from collective use via cooperation [*Ostrom*, 1990]. However, whether solutions are achieved by private mechanisms or public mandates, constructing strategies to achieve equitable groundwater allocation requires quantitative tools for planning and policy evaluation that integrate modern simulation methods with a new generation of management tools based on physical, institutional, environmental, and economic metrics that reflect decision-making objectives and processes.

Interestingly, the lead paper in the first issue of *Water Resources Research* addressed the treatment of social costs and benefits in evaluation of policy decisions for water investments [*Arrow*, 1965]. Quantifying economic impacts remains a relevant and evolving area of research as social welfare and ecosystem services are now being recognized as critical elements of water resource allocation decisions. Efforts to quantify human and environmental well-being are being taken into account when making investments in water infrastructure and natural capital, particularly when groundwater, a common pool and transboundary resource, is concerned [*Brauman et al*., 2007; *Guswa et al*., 2014].

Here we discuss recent advances and needs in groundwater management analytic tool development aimed at identifying aquifer exploitation and protection strategies that satisfy logistical, economic, environmental, and regulatory constraints. Such models can be used to quantitatively evaluate the impacts of proposed policy instruments such as taxes, quotas, and water rights structures, and management mechanisms such as water markets or reallocation strategies. Works that discuss the categories and techniques for coupling simulation with optimization methods used to guide aquifer management may be found in *Gorelick* [1983, 1990], *Yeh* [1992], *Wagner* [1995a], *Ahlfeld and Mulligan* [2000], *Mayer et al*. [2002], *Orr and Meystel* [2005], *Nicklow et al*. [2010], *Peralta* [2012], *Reed et al*. [2013], and *Singh* [2012, 2014a].

The endeavors of the hydrologic science community have broadened to improve our understanding and quantify physical and chemical processes involving groundwater. Research has also expanded its reach to develop management and policy evaluation tools incorporating modern simulation approaches combined with a multitude of optimization, heuristic, and multiagent system simulation methods. Indeed, hydrologic-economic models have been developed that represent water systems coupled with human behavior. Understanding the intricate interplay between hydrologic response and human activities is essential if groundwater resources are to be produced sustainably, or otherwise managed to reduce short-term vulnerability. Although aquifer simulation-management tools exist and are steadily being enhanced to handle more complex dynamics, the hydrologic science and water management communities are not keeping pace with what is necessary to halt and resolve systemic long-term effects of depletion and degradation of groundwater resources. Resolving these problems often requires institutional and regulatory changes that can be guided, in part, by assessments based on integrated hydrologic-economic models.

2. Evolution of Simulation-Optimization Approaches

Mathematical programming techniques are among the earliest and most commonly used for optimal groundwater management. In common, they share formulations involving a goal that attempts to minimize or maximize a single-objective or multiobjective function, subject to a series of constraints on variables describing the state of the system, such as hydraulic heads or concentrations, as well as limits on dependent and decision variables, such as pumping and recharge rates. Methods include (1) linear programming (LP) and quadratic programming (QP) [e.g., *Aguado and Remson*, 1974; *Maddock*, 1972a]; (2) nonlinear programming (NLP) [e.g., *Gorelick et al*., 1984; *Ahlfeld et al*., 1988a, 1988b]; (3) mixed integer linear and quadratic programming (MILP/MIQP) [e.g., *Maddock*, 1972b; *Rosenwald and Green*, 1974; *Willis*, 1976, 1979]; (4) mixed integer nonlinear programming (MINLP) [e.g., *McKinney and Lin*, 1995]; (5) differential dynamic programming (DDP) [e.g., *Jones et al*., 1987; *Andricevic and Kitanidis*, 1990; *Chang et al*., 1992; *Culver and Shoemaker*, 1992; *Sun and Zheng*, 1999; *Hsiao and Chang*, 2002]; and (6) stochastic nonlinear programming (SNLP) [*Wagner and Gorelick*, 1987, 1989; *Chan*, 1993]. LP is applicable only when the aquifer simulation model and objective function are both linear. When neither of them can be treated as linear, QP, or full NLP must be applied. In optimization problems where discrete decision variables such as well locations and fixed capital costs are involved, MILP, MIQP, or MINLP is used. DDP is particularly efficient for optimization problems with a large number of management periods. SNLP is able to overdesign pumping and injection systems to account for uncertainty in state variables, such as solute concentrations, and in spatially variable physical model parameters, such as hydraulic conductivity.

Linear programming is computationally efficient and has been implemented in a number of practical simulation-optimization codes such as MODMAN [*Greenwald*, 1998], MODOFC [*Ahlfeld and Riefler*, 1999], and the Management Process for MODFLOW [*Ahlfeld et al*., 2005], all of which involve hydraulic head, drawdown, and flow-related constraints. The major limitation of linear programming is that the method is technically restricted to confined aquifers, or more generally to systems in which saturated aquifer thickness does not depend on hydraulic head. In addition, linear programming generally cannot deal effectively with solute concentration management. Nonlinear programming and dynamic programming have much wider applicability. However, it is necessary in these methods to evaluate the derivatives (gradients) of the objective function and constraints (Jacobian, sensitivity coefficients) with respect to the decision variables (and also the state variables for DDP); this is the reason that these approaches are often referred to as "gradient-based" methods. The gradient can be computed analytically or numerically using finite differences.

Although gradient-based methods can be advantageous in terms of computational ease, they have some significant limitations as well. First, if the objective function and/or constraints are highly complex and nonlinear, there may exist multiple local optimal solutions. As a result, gradient-based methods may be trapped in a local optimum when a single starting solution is provided, thus failing to identify the globally optimal solution. Second, gradient calculation is a major source of numerical expense and difficulty, and convergence may be slow as a result.

Since the 1990s, a class of optimization methods based on heuristic search techniques have been developed and applied to groundwater management problems, including simulated annealing, genetic algorithms, tabu search, artificial neural networks, and outer approximation. These optimization techniques have been collectively referred to as global or evolutionary optimization methods. They are able to identify the global or near-global optimum. They have also been called "gradient-free" heuristic search methods because they do not require calculation of a gradient. Some of these methods mimic certain natural systems, such as biological evolution in the case of genetic algorithms, to identify the optimal solution instead of being guided by gradients of the objective function. Even so, some elements of gradient-based search can be incorporated into a global optimization framework. General references on global optimization methods include *Goldberg* [1989], *Sen and Stoffa* [2013], and *Glover and Laguna* [1997].

Global optimization methods generally require intensive computational effort. However, in spite of this, they have been widely used to solve groundwater management problems because of their ability to identify the global optimum, their efficiency in handling discrete decision variables such as well locations, and the ease and generality with which they can be linked with flow and transport simulation models. Earlier examples of the application of simulated annealing to remediation design optimization problems include *Dougherty and Marryott* [1991], *Rizzo and Dougherty* [1996], and *Wang and Zheng* [1998]. Examples of the application of genetic algorithms include *Wang* [1991], *McKinney and Lin* [1994], *Wagner* [1995b], *Huang and Mayer* [1997], *Wang and Zheng* [1997], *Aksoy and Culver* [2000], *Reed et al*. [2000], and *Smalley et al*. [2000]. Examples of the application of artificial neural networks include *Ranjithan et al*. [1993], *Rogers and Dowla* [1994], and *Aly and Peralta* [1999]. The first applications of outer approximation and tabu search to groundwater problems are presented by *Karatzas and Pinder* [1993] and *Zheng and Wang* [1996]. Recent reviews of global and evolutionary algorithms for both single-objective and multiobjective optimization for groundwater management can be found in *Nicklow et al*. [2010], *Peralta* [2012], and *Reed et al*. [2013].

3. Six Dimensions of Groundwater Vulnerability

Global change continues to adversely affect groundwater resources [e.g., *Aeschbach-Hertig and Gleeson*, 2012; *Kløve et al*., 2013]. The cumulative impacts of increasing population, urbanization, increased water use with prosperity, land-use change, inexpensive drilling and pumping technology, industrialization, expansion of irrigated agriculture, institutional changes, stricter water quality standards, and perhaps the early influence of climate variability, have led to widespread, often unmanaged, use of groundwater throughout the world. Even in the U.S., self-supplied groundwater use is rarely metered [*Maupin et al*., 2014]. Aquifers are the ultimate long-term reservoirs that both store and transmit freshwater. Aquifers are largely free of evaporation, regionally ubiquitous, and are generally free of pathogens under natural conditions. For these and

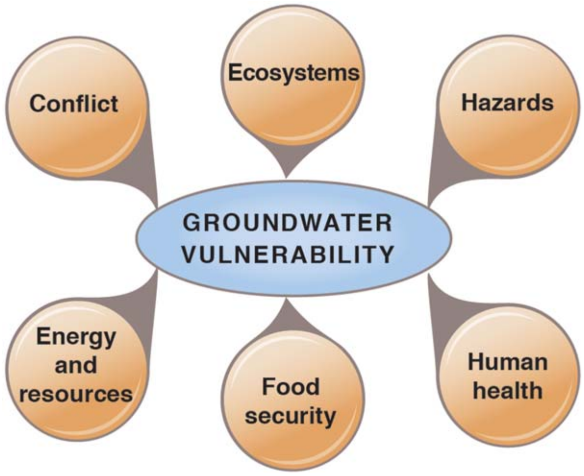

Figure 1. Dimensions of human and environmental vulnerability stemming from the exploitation and contamination of groundwater resources.

other reasons, aquifers serve as a valuable human and environmental resource, and it is unfortunate that groundwater overexploitation and contamination problems have become so widespread.

We inspect six dimensions of vulnerability spanning the connected human-environmental system. Figure 1 shows these six major dimensions, which reflect key interactions between groundwater resources and humans as well as the natural environment. Some works that consider complex problems involving, for example, environmental impacts, human health risk, and agricultural profits, fall into more than one category. In the following subsections, we discuss each dimension as it relates to historical drivers, citing selected recent research developments and key applications. We also suggest research needs for improved aquifer management.

3.1. Ecosystems

With over 47,000 dams in the world of which over 22,000 are large dams [*Gleick*, 2014], most of the world's large river systems are greatly affected by human use. As of 2005, over half of the world's large river systems suffered from the impacts of dams, even though surface reservoirs have provided notable benefits to humans and protected ecosystems from invasive aquatic species [*Nilsson et al.*, 2005]. Given the extent of managed surface waters around the world, groundwater exploitation has increased and the influence of groundwater use on rivers has been pronounced. Pumping from aquifers has affected groundwater-dependent ecosystems (Figure 2), disturbing the balance between human and environmental needs [*Margat and van der Gun*, 2013].

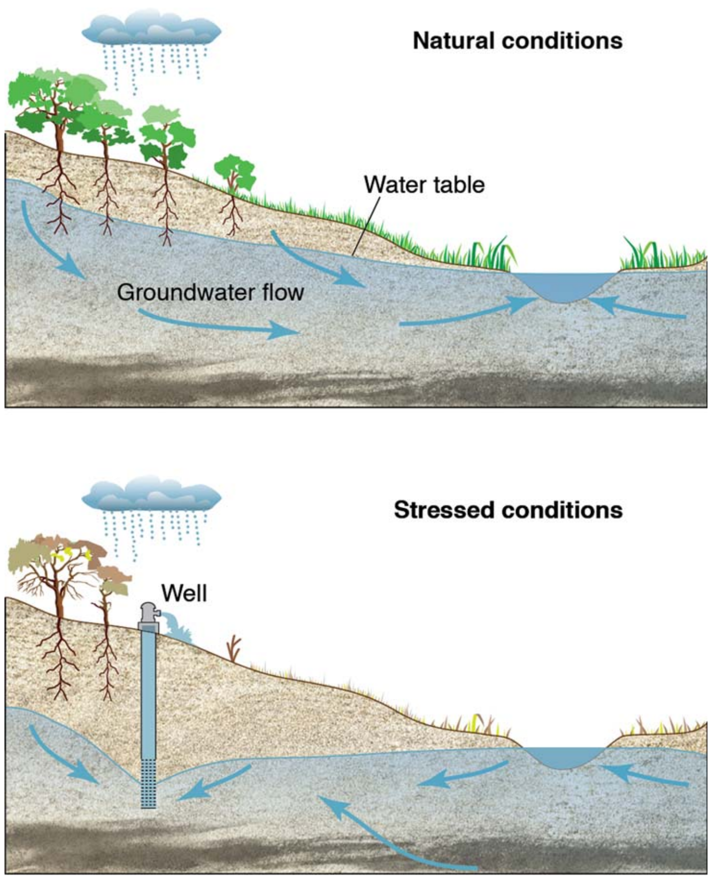

Figure 2. Impacts of pumping on groundwater-dependent ecosystems.

A modern example implementation of a simulation-optimization approach to mitigating ecological damage is in southwest Florida. As a consequence of excessive groundwater pumping during the 1970s and 1980s, groundwater withdrawals are regulated by the Southwest Florida Water Management District, which proposed specific minimum water levels in 1998 to protect lakes and palustrine (inland) wetlands by maintaining water levels at key aquifer compliance points. To provide the community's needs for groundwater, yet respect the constraint of maintaining the integrity of lakes and wetlands, the regional purveyor of water, Tampa Bay Water, which is Florida's largest wholesale water supplier, providing water to over 2.3 million people, runs an innovative, sophisticated, coupled aquifer simulation-optimization model known as OROP (Optimized Regional Operations Plan). Using simulation combined with LP, OROP determines a pumping rotation schedule on a weekly basis among 11 different regional well fields in conjunction with allocation of surface water and desalination plant water through a regional pipe network [*Wanakule and Adams*, 2014]. By regionally rotating pumping, wetland water levels have time to recover and the necessary temporal, typically seasonal, pattern of water levels (hydroperiod) is maintained. Tampa Bay Water's approach is a model system for satisfying water supply needs in the face of ecohydrologic constraints. Tampa Bay Water is constantly improving OROP and is actively considering sources of uncertainty that affect water security.

Motivated by the Tampa Bay Water system, *Feyen and Gorelick* [2004] developed a stochastic simulation-optimization model, SNLP, that maximized pumping while protecting wetland water levels that considered uncertainty due to heterogeneity in hydraulic conductivity. A Bayesian framework based on a similar system employed a simulation-optimization approach that determined tradeoffs between the worth of collecting additional hydraulic conductivity data and maximizing profits to a water purveyor while protecting ecologically sensitive wetlands [*Feyen and Gorelick*, 2005].

Perhaps the greatest misconception in groundwater management, which has a significant impact on the environment, is that the predevelopment magnitude of aquifer recharge is assumed to be equivalent to the sustainable rate at which an aquifer can be exploited. This misconception has been referred to as the "water budget myth" [*Bredehoeft et al*., 1982; *Bredehoeft*, 2002]. The consequent miscalculation is that "sustainability equals pre-development natural recharge," which ignores the fact that, prior to pumping, this virgin recharge was already discharging to rivers as base flow, to lakes, estuaries, and the ocean as bottom discharge, and to naturally occurring springs. To claim this quantity of groundwater recharge for human use via pumping can amount to double counting the available water that can be extracted safely for human activities on a long-term basis. Pumping can impact surface waters by reducing groundwater discharge to rivers as base flow or reversing flow directions thereby capturing surface waters. When pumping is initiated, water is primarily derived from changes in aquifer storage, and as pumping continues more and more water can come from boundaries [*Alley et al*., 1999]. The lag time between the initiation of pumping and the reduction in base flow or reversal of flow from surface waters can take many decades and achievement of a new equilibrium condition can take centuries [*Bredehoeft and Durbin*, 2009; *Bredehoeft and Alley*, 2014]. This lag time depends on the distance between pumping and (virgin) discharge points, the magnitude of pumping, aquifer geometry, as well as hydraulic properties, and other hydrologic factors. The consequence of ignoring the ultimate source of pumped water can be harm to groundwater-dependent ecosystems and to downstream water users.

A related source of confusion in groundwater management is the notion of *safe yield*. This often has been equated with either the entirety of natural aquifer recharge or a significant fixed proportion of it. Such false equivalence results in similar partial or complete "double counting" as noted in the above discussion of the "water budget myth." Fortunately, there is a valid concept of safe yield, but its definition depends on the particular system under consideration. In essence, safe yield is simply the magnitude of sustained pumping that could occur before something bad happens or "*without getting into trouble*" [*Lohman*, 1988]. Indeed, *Todd* [1958] stated, "The safe yield of a groundwater basin is the amount of water that can be withdrawn from it annually without producing an undesirable effect." Such negative consequences include excessive drawdown, promotion of land subsidence, unwanted alteration of hydraulic gradients or groundwater velocities, entrainment of seawater or contaminated water, or even social impacts such as promoting conflicts over competition for water.

Simulation-optimization studies have been conducted to explore alternatives for more sustainable or at least less vulnerable groundwater use, or *safe yield* as defined above. For example, *Yang et al*. [2001] presented a multiobjective optimization model based on the response matrix method and multistage linear programming to optimize management plans for groundwater resources in the semiarid River Shiyang Catchment in China. The optimization model was able to satisfy the environmental and economic objectives, but did not identify a final solution to reduce the overall water shortage within the catchment. *McPhee and Yeh* [2004] discussed a multiobjective optimization problem in which environmental objectives are explicitly considered by

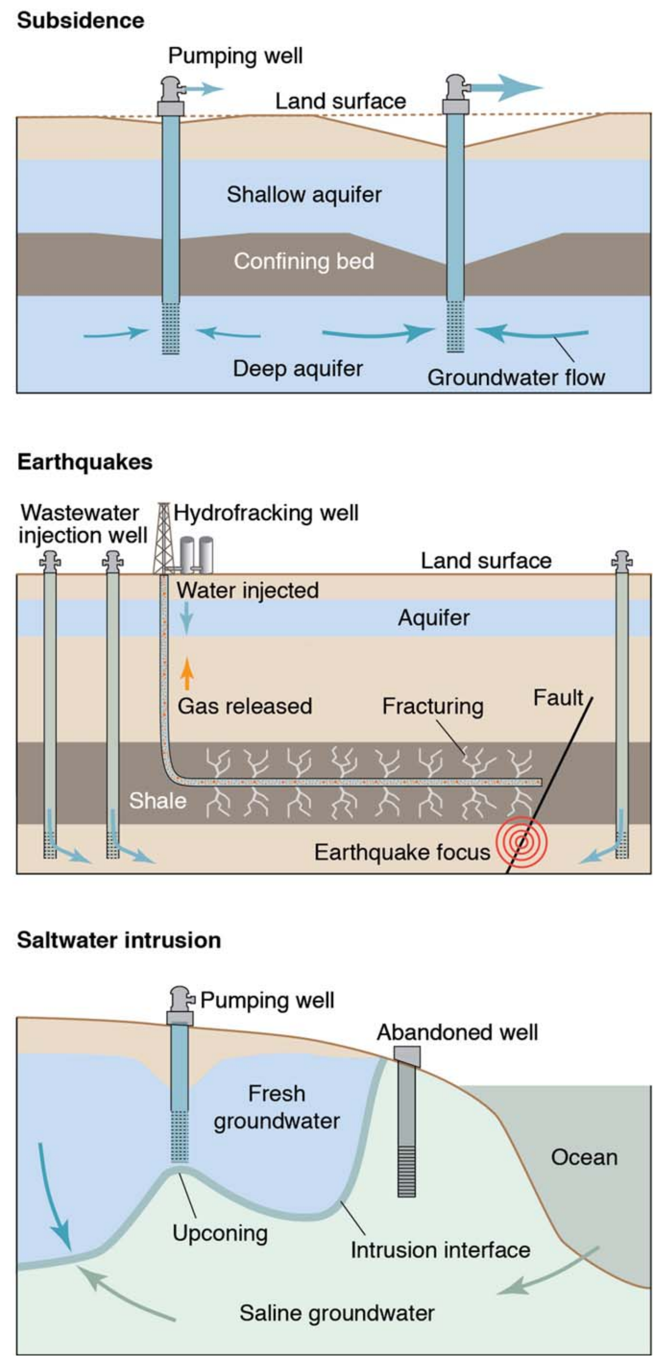

Figure 3. Hazards due to groundwater pumping and extraction include land subsidence (top), earthquake generation from wastewater injection (middle), and saltwater intrusion (bottom).

minimizing the magnitude and extent of drawdown within a specified region. The trade-offs among three competing objectives are derived and concepts based on fuzzy set theory are used to rank and select the alternative solutions.

3.2. Hazards

Scientific and engineering contributions to quantitative hydrogeology have grown steadily, largely in response to recognition of environmental hazards. There are a variety of hazards associated with overexploitation of aquifers (Figure 3): groundwater mining, land subsidence, triggered earthquakes, and seawater intrusion. Groundwater mining has resulted in aquifer depletion [*Harou and Lund*, 2008; *Gleeson et al*., 2012] on such a scale that its regional effects can be seen from space using gravitational anomaly [*Famiglietti*, 2014]. Major aquifers throughout the world are being exploited at extraordinary rates with the net global groundwater depletion rate doubling since 1990 [*Konikow*, 2011]. Regional hydraulic heads have declined 10s to well over 100 m (e.g., Houston, Texas 120 m, North China Plain 120 m, south-central Arizona 150 m, Chicago area 270 m, Sana'a basin, Yemen 70 m, Bin Gahir, Libya 80 m, Sierra de Cevillente, Spain 220 m) [*Cao et al*., 2013a; *Konikow*, 2013; *Margat and van der Gun*, 2013] with consequent aquifer depletion, excessive costs of pumping, and entrainment of deep saline water. Detailed calculations by *Konikow* [2011] suggest that dewatering of aquifers throughout the world has resulted in discharge to the oceans that accounts for about 13% of the observed rate of sea-level rise. *Liu et al*. [2008] applied a genetic algorithm to determine the maximum "sustainable pumping" that satisfies a series of prescribed constraints, including the maximum drawdown in the shallow water table aquifer in the North China Plain, which has been plagued by one of the most severe groundwater overdraft problems in the world [*Zheng et al*., 2010]. The genetic algorithm was also used to minimize the economic costs associated with groundwater pumping and different management scenarios.

In contrast, an opposite problem to excessive water table decline due to overexploitation of aquifers is a rising water table, resulting in excessive evapotranspiration, soil salinization, and flooding of subsurface structures. The simulation-optimization approach provides a valuable tool to manage engineering problems caused by shallow water tables. *Barlow et al*. [1996] identified optimal groundwater pumping strategies for controlling the shallow water table in the San Joaquin Valley, California in an attempt to sustain continued agricultural productivity. They demonstrated that the use of the combined simulation-optimization model resulted in a 20 percent reduction in the area that was subject to a shallow water table over that identified from simulation alone. *Bayer et al*. [2009] applied evolution strategies to control water table rises in the Emscher and Rhine Basin of Northwestern Germany that threatened local infrastructure and basements of buildings. They showed that through simulation-optimization modeling the existing well locations and pumping rates can be redesigned to meet the drawdown targets with substantial reduction, up to 25% in one scenario, in total extraction.

Groundwater pumping was known to cause land subsidence [*Poland and Davis*, 1969] and theory was in place by the middle of the 1900s [*Biot*, 1941; *Terzaghi*, 1943;]. But it was in the past 50 years that high profile causal links were dramatically demonstrated between over pumping and the hazard of land subsidence. Documentation of the subsidence of Venice, Italy [*Gambolati and Freeze*, 1979] served as a wake-up call and presented a quantitative simulation analysis of how coupled hydraulic and hydromechanical behavior can have dire consequences. Land subsidence has been documented in regions including Santa Clara Valley, California, Las Vegas, Nevada, Bankok, Thailand, the Mekong Delta, and the Yangtze Delta [*Cao et al*., 2013b]. Predictive models exist and are being used, as demonstrated by *Teatini et al*. [2006] who forecast a 10 year trend in land subsidence in the Emilia-Romagna coastland south of the Po River delta, Italy. *Larson et al*. [2001] were among the first to formulate an LP optimization model to determine maximum groundwater withdrawal from nine pumping sub-basins without causing irrecoverable subsidence during the forecast period. Formulation of an optimization problem involving land subsidence constraints was presented by *Chu and Chang* [2010] with earlier work that considered uncertainty by *Chang et al*. [2007].

A related geomechanical hazard involves waste water injection associated with petroleum production and consequent triggered or induced earthquakes [*McGarr*, 2014; *Yeck et al*., 2015]. In 2014, Oklahoma was host to more earthquakes than California [*Hand*, 2014]. Oklahoma had 190 earthquakes magnitude 3 or greater, or over 2.5 times the number in California. Evidence suggests that high volume wastewater injection wells were associated with 2547 small earthquakes near Jones, Oklahoma [*Keranen et al*., 2014]. Injection was also previously linked to a 5.7 magnitude 2011 earthquake in Prague, Oklahoma. Management of this hazard is ripe for a regulatory framework based on simulation-optimization. The collection of petroleum producers could have essentially a cap and trade system for pore-pressure increases in which simulation would be used to determine the likely pore pressure response, and geomechanical modeling is used to estimate the probability of induced earthquakes. The local and regional pore pressure could be managed to maximize fluid injection while minimizing injection-induced earthquakes.

A third hazard that has received a lot of attention for which simulation-optimization models have been developed relates to coastal seawater intrusion caused by groundwater pumping. Seawater intrusion has proven to be a significant threat to freshwater supplies around the world [*Werner et al*., 2013]. Contributions have explored a variety of methods for single-objective and multiobjective problems, and applied a variety of gradient and nongradient-based optimization methods that seek to control coastal drawdowns, hydraulic gradients, or salinity, with or without consideration of parameter uncertainty [*Willis and Finney*, 1988; *Cheng et al*., 2000; *Mantoglou et al*., 2004; *Park and Aral*, 2004; *Abarca et al*., 2006; *Bray and Yeh*, 2008; *Dhar and Datta*, 2009; *Haddad and Marino*, 2011; *Kourakos and Mantoglou*, 2013; *Al-Juaidi et al*., 2014; *Singh*, 2014b; *Sreekanth and Datta*, 2014; *Ataie-Ashtiani et al*., 2013].

3.3. Human Health

The threat of groundwater contamination came to light during the past 50 years. With nuclear energy produced since the 1950s in the U. S., storing spend fuel became a concern that resulted in a 1970 National Academy study [*National Academy of Sciences*, 1970] recommending permanent storage of high-level nuclear waste. At about the same time, groundwater contamination at Love Canal in New York state in the 1970s marked the beginning of an era in which the human health consequences of groundwater contamination were recognized. The Superfund program [*Comprehensive Environmental Response, Compensation, and Liability Act*, 1980] resulted in a focus on predictive and management technology research with the development of the field of contaminant hydrogeology and a major emphasis on aquifer remediation (Figure 4).

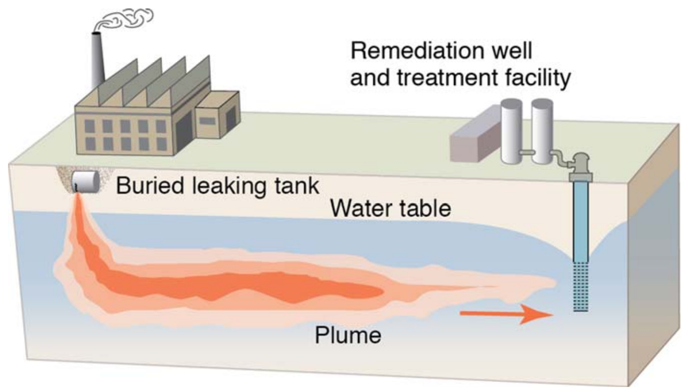

Figure 4. Protection from groundwater contamination using optimized pump and treat aquifer remediation.

Given the clear need to better design groundwater remediation systems, much work was done on simulation-optimization for contaminant capture and containment. Although hydraulic gradient control approaches using linear response matrices with linear or quadratic objective functions were in place by the mid-1980s [*Atwood and Gorelick*, 1985; *Lefkoff and Gorelick*, 1986; also see *Gorelick et al.*, 1993], it was recognized that treating concentrations as constrained variables in optimized remediation schemes required solute transport simulations combined with nonlinear programming, NLP [*Gorelick et al.*, 1984; *Ahlfeld et al.*, 1988a, 1988b]. Optimization methods then addressed model uncertainty using chance constraints and the multiple realization approach as well as optimal tradeoff between data collection and remediation costs [*Wagner and Gorelick*, 1987, 1989; *Tucciarelli and Pinder*, 1991; *Wagner et al.*, 1992; *Chan*, 1993] with applications to field problems in the U.S. and Canada [*Tiedeman and Gorelick*, 1993; *Gailey and Gorelick*, 1993].

In recognition of the highly complex and nonlinear nature of the objective functions and constraints in groundwater quality optimization problems, including both remedial and monitoring system design, a concerted effort has been made over the last two decades to develop and improve global optimization algorithms that are derivative-free and rely on heuristic and evolutionary search capable of identifying the global optimum. Some recent applications of these global optimization algorithms can be found in these studies [*Erickson et al.*, 2002; *Zheng and Wang*, 2002; *Becker et al.*, 2006; *Kollat and Reed*, 2007; *Shoemaker et al.*, 2007; *Nicklow et al.*, 2010; *Peralta*, 2012; *Reed et al.*, 2013; *Yang et al.*, 2013a].

Minciardi et al. [2007] presented an integrated approach to the sustainable planning and control of groundwater resources including groundwater quality. Physical and chemical models of the groundwater flow system are embedded as constraints in the optimization problem, which considers both control and planning decision variables. The resulting optimization problem is solved using nonlinear programming. *Bauser et al.* [2010] presented an optimal real-time control approach for the management of drinking water well fields. A numerical model is first used to represent the groundwater flow field. An ensemble Kalman Filter (EnKF) is then used to improve the model prediction by assimilating newly measured water level data and reducing the discrepancy between measured and simulated water levels. Next a multilevel optimal control method is formulated and solved to manage the water levels at artificial recharge locations to prevent potential contaminants from reaching the drinking-water wells. Human health risk was accounted for in a goal-programming simulation-optimization model of aquifer remediation [*Li et al.*, 2014]. Hydraulic barrier optimization was incorporated into a chance-constraint formulation that employed a Bayesian model to explore geologic uncertainty in remediation design [*Chitsazan et al.*, 2014].

Although much of the industrialized world has concentrated on anthropogenic sources of groundwater contamination, geogenic (naturally occurring) contamination by metals such as arsenic and chromium provide a pronounced risk to human health. Arsenic contamination is pervasive in southern and southeast Asia where over a hundred million people have been exposed [*Harvey et al.*, 2002; *Fendorf et al.*, 2010]. There is a great need to manage groundwater resources that are subject to such geogenic sources of contamination. For example, there is a need to determine optimal pumping rates and well-screen placement to avoid contaminant capture by municipal supply wells, and to combine real-time mixing control systems to dilute moderately contaminated water prior to delivery to the public [*Michael and Voss*, 2008; *Erban et al.*, 2013].

3.4. Food Security

Globally, just over 70% of all groundwater is used for irrigation [*Margat and van der Gun*, 2013], and about half of the world's irrigated crops rely on groundwater [*Famiglietti*, 2014]. In terms of land area, of the 301

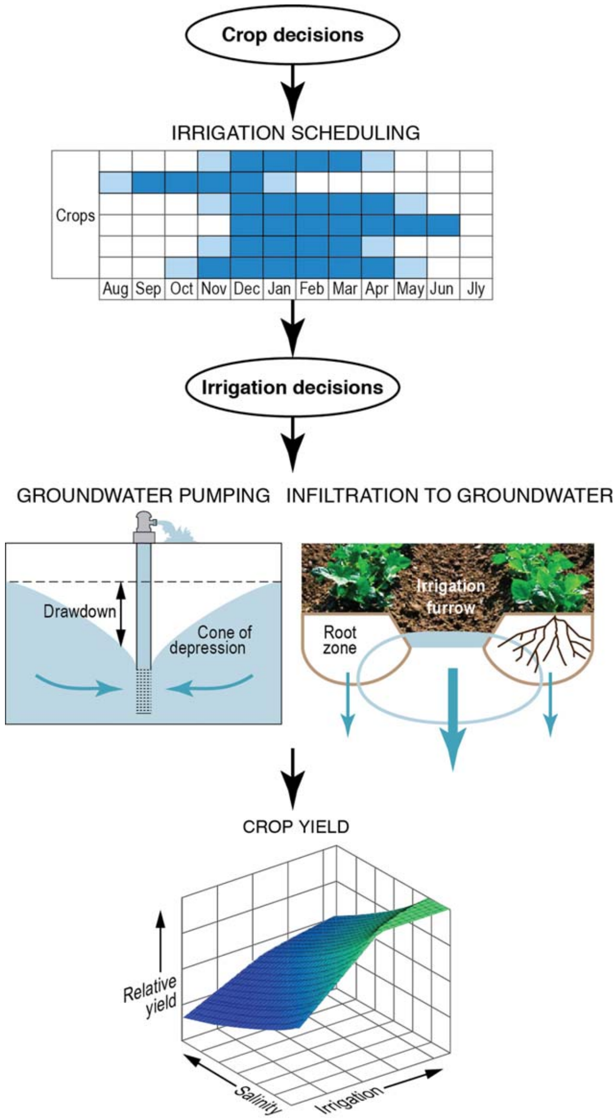

Figure 5. Agricultural-hydroeconomic components as part of a groundwater optimization model.

million ha equipped for irrigation globally, 38% depend on groundwater [*Siebert et al.*, 2010]. Generally, farmers have been fairly efficient in their use of groundwater in terms of supply, but this has not followed when it comes to managing contamination [*Bredehoeft et al.*, 1994]. It is not surprising that the field of simulation-optimization modeling (Figure 5) has its roots in agricultural water management with pioneering works by *Bredehoeft and Young* [1970] and *Young and Bredehoeft* [1972].

A limited amount of research has continued in management of groundwater allocation for optimal crop production, likely because the coupled hydrologic-agricultural economic models involved detailed and complex field applications. A coupled NLP conjunctive-use simulation-optimization model of an agricultural system, with explicit agronomic functions that considered water and salinity, was constructed to explore a water rental market among water-rich and water-poor farmers in the Arkansas River valley, Colorado [*Lefkoff and Gorelick*, 1990]. *Peralta et al.* [1994] developed an NLP for irrigation of corn in which pesticide leaching was constrained such that the reduction in crop production was minimized. *Schoups et al.* [2006] developed a conjunctive-use profit maximization model for the Yaqui Valley, Mexico, which produced 40% of the country's wheat until a major drought hit. The model identified the optimal cropping, reservoir release, and groundwater management policy. *Maneta et al.* [2009] developed a complex agricultural hydroeconomic model that maximized annual farming benefits subject to hydrologic relations developed by running a high-resolution coupled surface water—3-D saturated/unsaturated flow model. The integrated model incorporated production functions for crops that were rain fed or irrigated and was applied to the Sao Francisco River Basin in Brazil. Results quantified agricultural output under both mild and severe hypothetical drought conditions. *Khan* [2010] developed a combined 2-D-saturated flow and unsaturated flow model within the context of an NLP hydrologic-economic analysis of optimal paddy production in the southeastern Murray-Darling basin in Australia. *Gosh and Kashyap* [2012] used an ANN model for a groundwater system in India for optimal agricultural production. *Raul and Panda* [2013] presented a linear simulation-optimization of conjunctive use to identify the optimal pumpage and cropping at different levels of probability of exceedance of canal water availability and rainfall. Uncertainty in hydraulic conductivity was considered by *Pena-Haro et al.* [2011] in which four different stochastic hydroeconomic models were compared for optimal management of groundwater. Constraints were placed on nitrogen fertilizer application and the solution maximized the net benefits of agriculture, identifying least-cost fertilizer plans while meeting groundwater quality standards.

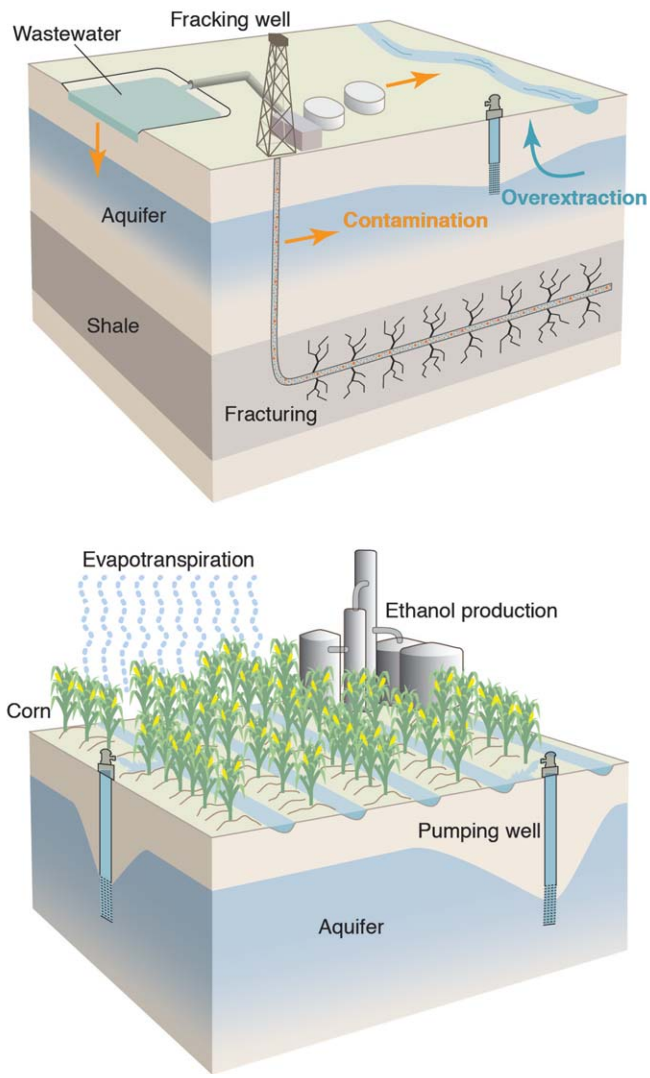

Figure 6. Vulnerability associated with simultaneous use of groundwater and petroleum recovery (top) and water use associated with biofuel/ethanol production (bottom).

3.5. Groundwater for Energy and Resources

In the U.S., groundwater extraction accounted for less than 1% of withdrawals for thermoelectric power [*Maupin et al*., 2014]. However, locally, groundwater and energy are intricately intertwined as the exploitation, delivery, and treatment of water requires energy, while almost all sources of energy require water for some aspects of production including extraction, cooling, or conveyance. This linkage, commonly referred to as the "water-energy nexus," has become a major focus in the hydrologic sciences [*National Research Council*, 2012; *Bartos and Chester*, 2014].

Groundwater management in the context of the water-energy nexus has taken on greater importance as shale oil and gas production has become a prominent feature in the United States' energy portfolio. Hydrofracking is the key technology that enables shale oil and gas production (Figure 6). Hydrofracking can require a significant amount of water, although this water need not be potable. It has been suggested that brackish injection water may be used more commonly in the future to avoid competition for freshwater [*Nicot and Scanlon*, 2012]. Installing and hydrofracturing a single well can take 7500–80,000 m^3 of water [*Meldrum et al*., 2013; *Vengosh et al*., 2014], with more water used recently per well as horizontal wells have extended over longer distances. In context, overall water use for shale-gas production is relatively small, e.g., in Texas $<$1% of total water use [*Nicot and Scanlon*, 2012]. *Scanlon et al*. [2014] state that hydrofracking does not, in general, use more water per unit of oil production than does conventional oil production. However, *Vengosh et al*. [2014] note that there are four potential risks to water resources of shale gas production: (1) contamination of shallow aquifers from stray gas and salinization of shallow groundwater through leaking natural gas wells, (2) the contamination of surface water and shallow groundwater from various sources of shale gas wastewater; (3) buildup of toxic and radioactive elements in soil or stream sediments; and (4) the overextraction of water resources promoting water shortages and conflicts. To date, there is no integrated simulation-optimization model formulation that accounts for all of these potential impacts.

In addition to shale oil and gas production, the increased use in the U.S. of biofuels, often considered "green" energy sources, also requires a significant amount of water for production (Figure 6). About 40% of U.S. corn is irrigated to produce ethanol [*Foley*, 2013], which has resulted in stress on regional aquifers. This is a significant concern for the Ogallala aquifer where corn irrigation is prominent, further depleting a stressed system. In addition, increasing demands for energy lead to increasing demands for water, and the lack of water resources can hamper energy production. It is imperative to manage water and energy

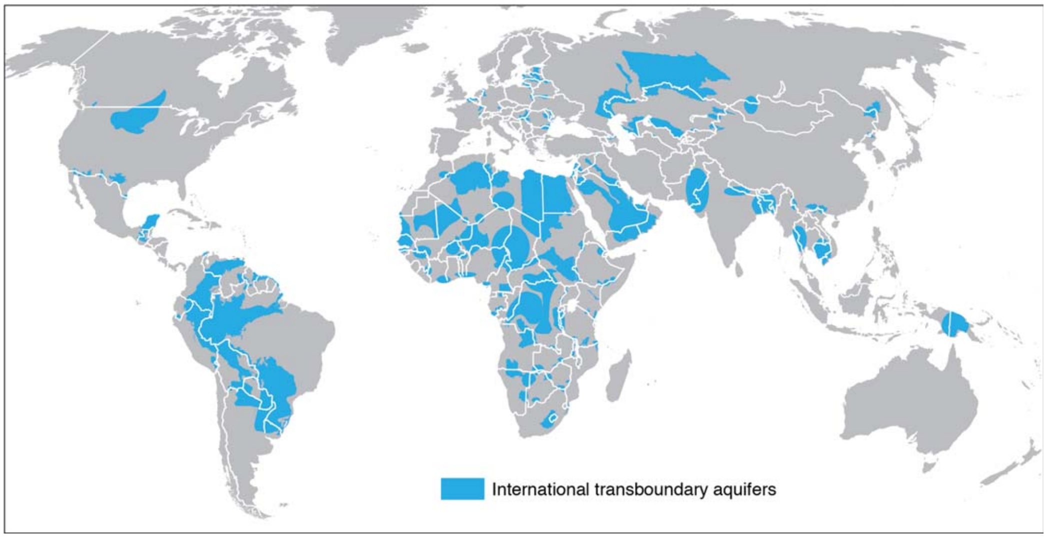

Figure 7. Conflicts can arise when international transboundary aquifers are exploited (data from *Puri and Aureli* [2009, update in 2012]).

resources jointly, considering water use during the entire life cycle of energy production. This problem is ripe for integrated hydrologic-economic model analysis.

Groundwater management plays an important role in water-energy nexus studies, although it is still rare to see application of the simulation-optimization framework in these types of studies. *Karimi et al*. [2012] presented a case study from Iran to explore how enhanced farm water management can help in reducing groundwater exploitation and subsequently limiting energy consumption and the carbon footprint of the groundwater economy. *Wang et al*. [2012] analyzed the electricity use of groundwater pumping for agriculture in 11 provinces of China and derived estimates of greenhouse gas emissions from groundwater pumping. They concluded that as China is moving aggressively to reduce water use to combat water scarcity, significant potential exists to promote the cobenefits of water and energy savings. Finally, a valuable summary along with analytic solutions for the important problem of minimizing energy costs for pumping by minimizing lift appears in *Ahlfeld and Laverty* [2011].

3.6. Conflict

There are many types of conflicts that arise from water use by multiple parties. Perhaps the greatest need for regional groundwater management is to help resolve transboundary groundwater conflicts. The scale of transboundary problems can be intraregional, interstate, or international. The underlying physical problem is similar in each case—groundwater exploitation in the portion of an aquifer on one side of a political or property boundary affects hydraulic heads and consequent pumping costs throughout the connected domain, and pumping can draw clean or contaminated water across such a boundary. International transboundary groundwater issues have received significant attention and are highlighted in several excellent papers [*Bloomquist and Ingram*, 2003; *Jarvis et al*., 2005; *Chermak et al*., 2005; *Fernandez*, 2006; *Darnault*, 2008]. A superb review of transboundary aquifers (Figure 7) including hydrogeologic, economic, legal, institutional, and environmental issues is presented by *Puri* [2001], and a comprehensive atlas of international transboundary aquifers was produced by *Puri and Aureli* [2009; also see 2012 map].

There have been only a few applications of coupled simulation-optimization models to this problem. An approach has been effectively developed for the Sahara aquifer shared by Algeria, Libya, and Tunisia suggesting extraction scheduling that is communally beneficial [*Siegfried and Kinzelbach*, 2006]. Such approaches could benefit countries that also share major aquifers such as Saudi Arabia and Jordan, which each mine the fossil Disi Aquifer that supplies regional agriculture and much needed groundwater to Amman. Interstate (regional) transboundary groundwater management models were developed for Greece [*Psilovikos*, 2006], and for a U.S. case involving Mississippi and Tennessee [*Cameron*, 2009].

Conflicts can also arise when water managers fail to meet their mandate to provide supplies to the public. The 2003–2004 drought in Chennai, India's sixth most populous city, led to the complete shutdown of the piped supply system for almost a year. To cope with more typical undersupply, 420,000 mostly private wells have been drilled in the city, and yet many of them went dry during this period. With all of the surface reservoirs depleted and limited municipal groundwater pumping capacity, the failure of the water manager led to the emergence of private tanker trucks delivering high-cost water to the 4.5 million inhabitants until the resumption of monsoonal rains. A multiagent model was able to capture the dynamics of this system and explore the benefits of rooftop rainwater harvesting as well as quantify current and future vulnerability to potential drought recurrence [*Srinivasan et al*., 2010a, 2010b, 2012].

4. Perspectives on Future Research Needs

4.1. Historical Context

The historical research and implementation focus of groundwater simulation-optimization models has been divided into two types of problems: engineering design and hydroeconomics. Engineering design tends to involve hydraulic problems such as optimal capture and containment of a contaminant plume or dewatering of an excavation. Objectives typically minimize costs or surrogates for costs, such as pumping rates and lifts or the volume of contaminated water removed, or pumped, treated and re-injected. Hydroeconomics consider problems at the interface between hydrology and human behavior and is used primarily for policy evaluation. In general, these models have combined groundwater or integrated groundwater-surface water models with optimization methods to understand the interactions among physical and chemical processes, and economics, in response to policy instruments. Such models can provide valuable insight into the likely influence of taxes, quotas, regulations, water allocation strategies, water rights structures, and water markets on system reliability, resilience, and sustainability.

4.2. Strategic Research Needs

4.2.1. What Should be the Thrust of Continued Research?

A critical avenue for research is representing complex coupled human-natural systems. Understanding the multifaceted interactions among social, biophysical, and engineering factors that determine the availability of water resources is crucial to identifying sustainable trajectories for future development [*Sivapalan et al*., 2012]. Although a vast body of research exists in different and sometimes fragmented subfields, future efforts need to address the interactive and synergistic effects of multiple natural and human factors on short-term groundwater vulnerability and long-term resource sustainability. Within this context, innovative approaches and techniques should be developed to allow for consideration of climate and land-use change, urbanization, economic development, ecohydrology, and logistical constraints in groundwater management. This huge undertaking represents a major challenge for the hydrologic research community, and the need for an integrated system framework is necessary for environmental assessments aimed at reducing vulnerability in a move toward sustainability [*Liu et al*., 2015].

Sustainable water management can be considered a part of an integrated hydrologic-ecological-economic system at the river basin scale [*Cheng et al*., 2014]. Within this framework, groundwater and surface water are managed as a single resource with simultaneous consideration of food, ecosystem, and water security. Because of the complexity and computational intensity in the type of simulation models usually needed to represent a coupled system, the surrogate modeling approach is well suited to derive an approximate but highly efficient simulation engine that may be run many hundreds of times by an optimization algorithm. The optimization component also needs to be very flexible and efficient, able to accommodate both natural and human dimensions [e.g., *Cai*, 2008; *Cai et al*., 2015].

Although many problems can be formulated within a constrained optimization framework, there are many that involve hierarchical decision-making, rules, learning, traditions, and compromise. To handle policy evaluation and water allocation in these highly complex human-natural systems, an optimization framework is likely to be overly restrictive. Multiagent models provide a path forward as certain agents, such as farmers, may be represented as risk averse profit maximizers, while other agents, such as water managers, may operate under conditions of constant tradeoffs based on a set of rules with no clear or necessary optimization strategy.

The agent-based model (ABM) has emerged as a versatile approach to represent the coupled human-natural system (CHNS), a term first used by *Liu et al*. [2007]. ABMs define the relationships between simple individual behaviors, collective structures, and interactions with the environment [*Macy and Willer*, 2002]. The agents in an ABM are autonomous entities characterized by internal goals and behavioral rules. Agents interact with one another and with the natural and institutional environment shared by all agents. In systems modeling, there is often a distinction made between ABMs and Multiagent Systems (MASs), where ABMs are those in which agent behavior results in an emergent property (such as bird flocking behavior), while MASs represent complex interactions among agents and system-wide responses but do not necessarily result in an emergent property of the system. Recently, MASs have been applied to hypothetical basin management involving surface water supply [*Yang et al.*, 2009], but there have been very few applications to groundwater management modeling. The analysis of the Chennai, India water crisis (see section 3.6 Conflict) by *Srinivasan et al*. [2010a, 2010b] employed a multiagent modeling framework coupled to a groundwater model to represent the behavior of the water manager, the private water tanker operators, and user demand for water. Water users occupied successive categories based on their physical and economic access to types of supply and ability to store water. These water users were able to migrate to higher access categories as their incomes grew over time. *Mulligan et al*. [2014] present a MAS for assessing groundwater policy in which the economic decision models are coupled with a physically based groundwater flow model. Their study of the Republican River overlying a portion of the Ogallala aquifer demonstrates the challenges when coupling realistic hydrogeology and human behavior models to assess groundwater management policies.

With the exception of economists, the broader social science community has been reluctant to embrace the integrated human-biophysical optimization or MAS modeling effort. The reasons are undoubtedly many, but two explanations are that there are those in the noneconomics branches of the social sciences who: (1) do not rely on mechanistic/process models, so translating their expertise into a quantitative representation is an obstacle, and (2) believe that it is not possible to "model society," which they perceive as the goal of MAS or other integrated models. The hydrologic science community can deal with the first obstacle by working more closely with social scientists to better quantify actions and reactions for which they have insight. Regarding the second impediment, it is a misrepresentation to claim that the integration approach is attempting to model society. Rather the goal is to successfully represent coupled biophysical-human responses, which one can do by predicting outcome or estimating the probability of outcome of a group process. One need not represent every individual conversation, debate, or negotiation to predict likely outcomes. Water users and water managers typically have good reasons to operate the way they do. They have certain predetermined needs and rules, seek to maximize net benefits, and want to contain risks by investing in some form of insurance (e.g., overdesign, excess pumping, or storage capacity) to reduce potential loss due to their vulnerability. Outcome of the coupled human-natural process can be quantified and integrated into a policy evaluation framework for water allocation. Some inroads have been made along these lines, but they have been restricted to issues that are ultimately linked to economics rather than other fields of social science, such as history, human geography, anthropology, political science, or psychology.

4.2.2. In Which Locations and Environments Should the Hydrologic Science Community Focus its Efforts?

The regions for which there are tremendous benefits from simulation-optimization models are those that (1) are highly groundwater-dependent, (2) where large-scale transboundary water issues are paramount, and/or (3) in which the common pool resource needs to be managed. These categories are not mutually exclusive. Groundwater dependency can be for human needs and involve vulnerability associated with hazards, human health, food security, and energy or other natural resources. Transboundary and common pool groundwater use create vulnerability due to potential conflict. Groundwater-dependent ecosystems require decisions on how to best balance environmental and human needs. All these are problems involving a set of objectives and constraints, prerequisites for application of simulation-optimization. In addition, policy evaluation and allocation problems can be so complex that current simulation and optimization methods may be insufficient (e.g., inefficient or ineffective) to be useful. Therefore, a need exists for technical research advances aimed at improving the ability to better account for all relevant modeled processes (structural uncertainty), deal with unrepresented variability in existing model representations (parameter uncertainty), and enhance model performance (efficiency).

4.3. Technical Research Needs

4.3.1. Integrating Uncertainty and Risk

Most natural groundwater systems are characterized by significant heterogeneities in the physical and chemical properties of the aquifer systems. Such heterogeneities pose a major difficulty to groundwater management modeling. No management strategies can be "optimal" if the aquifer simulation model has not been reliably calibrated. In fact, no matter how thoroughly a simulation model is calibrated, it always has some degree of uncertainty in both model input and output. Moreover, substantial uncertainties are always present in the economic and policy factors. Thus, how to adequately accommodate the uncertainties in simulation and economic models has long been a focal point in groundwater management modeling since it became an active research subject. This topic will likely remain a major area of future research as groundwater management modeling is increasingly integrated into broader coupled human-natural systems to address multifaceted water management problems of today and tomorrow.

Traditionally, stochastic programming has been commonly used to account for the uncertainties in aquifer properties. The two main approaches are inclusion of probabilistic formulations using chance constraints by predefining a constraint reliability level [*Wagner and Gorelick*, 1987; *Sawyer and Lin*, 1998] and the "stacking" approach in which multiple realizations of an uncertain aquifer parameter such as hydraulic conductivity are generated and the management model simultaneously satisfies the constraints for all realizations [*Wagner and Gorelick*, 1989; *Chan*, 1993, *Wagner et al*., 1992, *Pena-Haro et al*., 2011]. *Morgan et al*. [1993] combine the stacking approach with chance constraints in an LP formulation. Whenever the stacking approach is used, the solution reliability (one minus the probability of failure) is a nonlinear function (approximated as $n/(n+1)$) of the number of simultaneous realizations, n, considered in the constraint stack [*Chan*, 1993]. The computational cost is proportional to the number of realizations. Because NLP is used to solve the problem, a global optimum is not guaranteed.

However, when a global optimization algorithm is used with the stacking approach, which may require hundreds of simulation runs for each realization, the approach is computationally burdensome. Besides the surrogate model approach previously discussed, other innovations are needed to make assessment and incorporation of uncertainties more computationally tractable. Examples of past works include intelligent "stack ordering" of realizations to identify and use only a most critical subset of all realizations in the optimization process [*Bayer et al*., 2008] and development of the so-called "noisy genetic algorithm" to significantly reduce the number of realizations required in the application of a simple genetic algorithm [*Smalley et al*., 2000; *Wu et al*., 2006].

Relative to the above multirealization approach, several techniques have been used to quantify the uncertainties in a complex simulation model with far less computational burden. *Andricevic and Kitanidis* [1990] were the first to use DDP to optimally stage aquifer remediation while gathering and updating hydraulic (conductivity) and transport (dispersivity) values. *Lee and Kitanidis* [1991] applied the ensemble Kalman filter (EnKF), using real-time aquifer measurements to simultaneously estimate hydraulic parameters while determining remediation decisions. *Chen and Zhang* [2006] present a highly efficient EnKF algorithm for uncertainty quantification and data assimilation. *Hendricks-Franssen and Kinzelbach* [2008] introduced an improved EnKF by reducing the filter inbreeding problem. The probabilistic collocation method is another computationally efficient method for uncertainty analysis that has been applied to groundwater models [*Li and Zhang*, 2007; *Wu et al*., 2014]. It can be expected that these methods will become more widely adopted and used in groundwater management modeling in the future.

A fundamental technical challenge for groundwater management modeling is to translate uncertainties from multiple sources, including aquifer properties, future climate forecasts, water demand projections, land-use change, and economic valuation of water, into decision support systems that quantify risk and are easy to use by policy makers and water managers. Risk-based engineering design compares predetermined pumping/remediation scenario costs (including regulatory penalties), benefits, and probability of failure (developed by *Massmann and Freeze* [1987]; also see the comprehensive review by *Tartakovsky* [2013]). Such methods quantify risk very well, but do not generally result in optimal hydraulic schemes. A discussion of how such formulations compare to simulation-optimization based ones, and how optimization can be joined with risk-based formulations is presented in *Freeze and Gorelick* [1999]. *Harou et al*. [2009] provide an overview of coupled hydrologic-economic models that integrate spatially distributed water resource systems, infrastructure, management options, and economic values to provide policy insights and better management strategies. A continuing need for the future in the groundwater management arena is to develop conceptually integrative and computationally efficient management modeling tools that are capable of considering predictive uncertainty in the face of multiple threats posed to groundwater quantity and quality, plus the physical (geophysical) and economic effects of overexploitation.

4.3.2. Mitigating Computational Burdens

The simulation models required to represent highly coupled hydrologic processes, especially those involving ecological systems, are becoming increasingly complex and computationally demanding. This is especially true when a global optimization algorithm must be employed to deal with nonlinear and local optima problems requiring hundreds of simulation model runs in a global algorithm.

In the past, efforts to mitigate the computational burden have generally followed two paths. One is to combine elements of gradient-based LP or NLP with a global algorithm at different stages of optimization. The other is to construct a response surface or surrogate model to replace the simulation model in the simulation-optimization framework. *Zheng and Wang* [1999] present an integrated approach in which a global optimization algorithm, tabu search, is used to find the optimal well locations, while linear programming is used to find the optimal pumping rates. In essence, the large mixed integer problem is decomposed into smaller subproblems, each of which has a much smaller number of decision variables so that the optimal solution can be reached much faster. *Aly and Peralta* [1999] combine artificial neural networks with a genetic algorithm to reduce the number of forward simulations required. The idea is to use an artificial neural network to construct a response function after a certain number of forward simulations have been performed, and then use this approximate response function in lieu of typical linear response functions created directly from a simulation model.

In more recent works, surrogate-assisted approaches have been formally introduced to greatly reduce computationally expensive global optimization algorithms [*Regis and Shoemaker*, 2009, 2013; *Muller et al*., 2013; *Wild and Shoemaker*, 2013]. This is accomplished by constructing a surrogate model (response surface) to select candidates for integer and continuous decision variable points at which the computationally expensive objective and constraint functions are to be evaluated. In the future, continuing efforts should be made to develop novel methodologies aimed at improving the computational efficiency of optimization algorithms. Surrogate-assisted algorithms discussed above represent a major research direction. Various forms of surrogate modeling summarized by *Razavi et al*. [2012] may be used in the simulation-optimization framework. Because of the inherently parallel nature of global optimization algorithms, development of parallel algorithms, including high-performance cloud computing platforms, is another important direction for further research [e.g., *He et al*., 2007; *Hunt et al*., 2010; *Yang et al*., 2013b].

5. Managing Unsustainable, Vulnerable, and Sustainable Groundwater Systems

Aquifer management models can be of benefit to water resources planning and allocation policy evaluation in different ways depending on whether groundwater system use is unsustainable, vulnerable, or sustainable. Where fossil aquifers are being mined unsustainably, or where aquifers with minimal recharge and inconsequential natural discharge are being tapped, the trajectory of economic depletion can be managed for a so called "soft landing." Major nonrenewable aquifer systems exist throughout portions of the (water-scarce) world, including the Saq and Arabian platform system including the Disi aquifer in the Middle East, the Murzuk Basin, Lake Chad Basin, and Nubian Aquifer in northern Africa, the Great Artesian Basin in Australia, the West Siberian Artesian Basin in Russia, and the Basin and Range aquifers of Arizona in the U. S. [*Margat and van der Gun*, 2013]. Societal goals reflecting agricultural production needs can be coupled to groundwater models to minimize physical, economic, and social impacts over time, with the understanding that continued use of the resource is indeed untenable. In regions where aquifer storage is large, the planning horizon for aquifer mining will be multigenerational, potentially lasting hundreds of years.

Turner et al. [2003] define vulnerability as "the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stress/stressor." Vulnerability is a response to a shock and is distinctly different from long-term unsustainability. Simulation-optimization is perhaps best suited to help identify strategies to reduce vulnerability by running the model under a suite of counterfactual conditions and targeting resilient solutions. Water planners can then select the course of action that meets their risk tolerance.

A sustainable groundwater system is one in which pumping can safely continue indefinitely. If water managers adopt the definition of safe yield as the maximum prolonged pumping such that all logistic, environmental, legal, social, economic, and physical constraints are met, then sustainable groundwater use solutions can be identified. However, the other essential requirement is a complete understanding of the future hydrogeologic system, including ultimate long-term capture of surface waters and rejected recharge, as well as water quality degradation. Aquifer management models provide the right framework to identify sustainable pumping policies, but it remains a challenge to satisfy both the need for a complete management problem formulation and a comprehensive groundwater model.

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