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Transition Pathways to Sustainable Agricultural Water Management: A Review of Integrated Modeling Approaches

Erin M.K. Haacker, Vaishali Sharda, Amanda M. Cano, R. Aaron Hrozencik, Agustín Núñez, Zachary Zambreski, Soheil Nozari, Garvey Engulu B. Smith, Lacey Moore, Sumit Sharma, Prasanna Gowda, Chittaranjan Ray, Meagan Schipanski, and Reagan Waskom

Research Impact Statement: Integrated modeling can be useful but must be put in context using field studies. Modelers need to work with stakeholders to include cutting-edge management techniques.

ABSTRACT: Agricultural water management (AWM) is an interdisciplinary concern, cutting across traditional domains such as agronomy, climatology, geology, economics, and sociology. Each of these disciplines has developed numerous process-based and empirical models for AWM. However, models that simulate all major hydrologic, water quality, and crop growth processes in agricultural systems are still lacking. As computers become more powerful, more researchers are choosing to integrate existing models to account for these major processes rather than building new cross-disciplinary models. Model integration carries the hope that, as in a real system, the sum of the model will be greater than the parts. However, models based upon simplified and unrealistic assumptions of physical or empirical processes can generate misleading results which are not useful for informing policy. In this article, we use literature and case studies from the High Plains Aquifer and Southeastern United States regions to elucidate the challenges and opportunities associated with integrated modeling for AWM and recommend conditions in which to use integrated models. Additionally, we examine the potential contributions of integrated modeling to AWM — the actual practice of conserving water while maximizing productivity. ***Editor's note****: This paper is part of the featured series on Optimizing Ogallala Aquifer Water Use to Sustain Food Systems. See the February 2019 issue for the introduction and background to the series.*

(KEYWORDS: groundwater; irrigation; water scarcity economics; decision support systems; soil health; water conservation.)

INTRODUCTION

One of the great challenges of our time is to safeguard the supply of water for food production (FAO 2011). This is generally approached through the adoption of farm management practices and technologies that are meant to increase water productivity, often cutting across traditional systems of study such as agricultural economics, hydrology, and agronomy. In the past several decades, individual scientific disciplines have developed models, both empirical and process-based, to investigate problems related to agricultural water management (AWM)

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Nebraska Water Center (Haacker, Sharda, Ray), University of Nebraska, Lincoln, Nebraska, USA; Department of Plant and Soil Sciences (Cano), Texas Tech University, Lubbock, Texas, USA; Department of Agricultural and Resource Economics (Hrozencik, Moore), Department of Civil and Environmental Engineering (Nozari), Department of Soil and Crop Sciences (Smith, Schipanski), and Colorado Water Institute and Water Center (Waskom), Colorado State University, Fort Collins, Colorado, USA; La Estanzuela Research Station (Núñez), National Agricultural Research Institute of Uruguay, Colonia, URY; Department of Agronomy (Zambreski), Kansas State University, Manhattan, Kansas, USA; Department of Plant and Soil Sciences (Sharma), Oklahoma State University, Stillwater, Oklahoma, USA; and Grazinglands Research Laboratory (Gowda), USDA Agricultural Research Service, El Reno, Oklahoma, USA (Correspondence to Haacker: ehaacker2@unl.edu).

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(e.g., Gisser and Sanchez 1980; Harbaugh et al. 2000; Neitsch et al. 2011). Advances in computational power enable researchers to assimilate more aspects of AWM into models, which in practice results in the need for models to encompass systems that intersect several disciplines. Rather than starting from scratch, research teams often choose to integrate existing models in whole or part (e.g., Kendall 2009; Barthel et al. 2012; Dodder et al. 2015; Bailey et al. 2016; Hrozencik et al. 2017, among many others). The combined models include more components of the agricultural system and allow researchers to minimize assumptions concerning system components that previously would have been modeled separately.

The purpose of this paper was to explore the relationship between a large and complex problem — AWM — and a large and complex tool — integrated modeling. Little work has been done to contextualize integrated modeling within the practical imperatives of water conservation at field and larger scales. We attempt to reconcile the needs of agricultural water managers with the opportunities afforded by integrated modeling.

Unlike many other reviews of integrated modeling, this article includes the perspectives of non-modelers. Scientists who build models may be less directly involved with data collection at the field level or with the application of modeling results. As models of a particular area are constructed, integrated, refined, calibrated, and validated, the people who work at the field and management scales are simultaneously developing innovative techniques for water conservation, thus changing the underlying processes that AWM models are designed to capture.

This paper attempts to fill the model-praxis gap by inspecting the relationship between integrated modeling and AWM, using examples from the High Plains Aquifer (HPA) and other regions. We identify situations in which integrated modeling is likely to be a good solution for challenges in irrigation management, and propose a decision tree to determine whether integrated modeling is the most appropriate approach to a problem. We also present a new explicit definition of integrated modeling and suggest research directions for integrated models to accurately reflect cutting-edge practices of AWM.

AGRICULTURAL WATER MANAGEMENT

Definition and Scope

AWM is the process of measuring, tracking, and adjusting the use of groundwater, surface water, and/or precipitation, to maximize the ratio of crop water uptake to evaporation, runoff, and deep infiltration (Smidt et al. 2016). Agronomic techniques for AWM depend on type of water source and its proximity, soil characteristics, and the amount and variability of seasonal rainfall, among many other factors. Although dryland agriculture also requires intensive water management, in this paper we focus primarily on AWM for irrigation management because irrigation is extractive and thus has a more direct impact on often limited or nonrenewable water resources than dryland farming. AWM is practiced in the context of the physical environment, economic constraints, and framework of governance (Smidt et al. 2016). AWM is highly contingent on the supply of water for irrigation, the seasonal variability and timing of rainfall, and the availability of insurance for drought-tolerant crops or limited irrigation schemes; it can also depend on whether producers operate on their own land or rent it, and if credit is available to invest in new technologies. Small changes can ripple through agroecosystems: a change in the United States (U.S.) Department of Agriculture's Dietary Guidelines, or the Department of Energy's biofuel targets, for example, can significantly change the incentives for growing different crops. A shift from distributed rainfall to concentrated rainfall, without changing the average growing season precipitation, can alter the amount of water that infiltrates into soil and groundwater vs. the amount that drains from the landscape.

The agricultural water cycle is highly complex, with potentially unintuitive linkages. For example, a crop that is fed fertilizer will demand more water than a nutrient-limited crop, and a diseased crop will demand less water (see Tanner and Sinclair 1983). Cover crops help to retain soil moisture in some areas, while depleting the same in other areas (Fageria et al. 2009). Efforts to save water through changes in management or infrastructure, such as canal lining and irrigation systems, can reduce withdrawals while still resulting in little net change in consumptive water use, because leakage "lost" from the canals was previously recharging the groundwater. New technologies, such as advances in high application efficiency irrigation or improved crop varieties, can enable full irrigation with less water, but since water users who adopt these practices will generally retain the same water rights, this "saved" water is often applied to other fields that may be water short (Smidt et al. 2016). Generally, conditions in soil, crop health, and nutrient availability vary below the field scale (Cano et al. 2018). Thus, interventions applied at one scale, such as the management of tailwater or center pivot wheel ruts, can be difficult to capture in the same policy or study as management at other scales, such as river flow requirements resulting from interstate compacts. While there is often a discrepancy between the scales of water management and agricultural markets (Hansen 2015), today's AWM, usually based on local water policies, will ultimately impact food supplies on a global scale.

Efforts in AWM span several magnitudes of scale, from individual producers' irrigation choices to basin-wide conservation policy implementation. For example, a producer might choose to adopt a more efficient irrigation application method to increase farm profit and reduce the costs associated with irrigation. This type of AWM aims to optimize water use at the farm level with little regard for basin-wide impacts. In contrast, a policy maker or water manager may aim to optimize water use at the basin level by balancing the cost of current water conservation with the benefits of increased water availability in the future. Previous research demonstrates that farm-level AWM can work against the objectives of basin-wide AWM in that enhanced irrigation efficiency can increase irrigation demands if more efficient technology induces adjustments along the extensive margin such as irrigating more land or planting more acreage of water-intensive crops (Pfeiffer and Lin 2014).

Crop water productivity, the crop yield per unit of water applied, includes both "blue water" (from rivers and aquifers) and "green water" (from precipitation and soil storage); this distinction enables irrigation efficiency to be considered as a separate indicator (Hansen 2015). To secure the highest possible crop water productivity in a given environment, other yield limiting factors (nutrients, weeds, pests and diseases, and pollutants) have to be optimally managed (Van Ittersum and Rabbinge 1997). AWM practices which promote and depend upon soil productivity by enhancing long-term soil health — defined as "the capacity of a soil to function" — and effective nutrient usage, which will become increasingly important in the next century (Karlen et al. 2017). In a simulation study, Ogle et al. (2012) predicted relatively high soil organic carbon (SOC) stocks in the western-central Great Plains due to the positive effect of irrigation on productivity, an effect that has been validated by observations (Gillabel et al. 2007; Denef et al. 2008). Although the effect of changes in soil organic matter on soil water holding capacity appears to be small (Minasny and McBratney 2018), the importance of soil health on crop production is undeniable and is magnified in situations where AWM policies result in a decrease in irrigation capacity.

Additionally, the promotion of certain management practices (crop rotations, conservation tillage, cover crops, forage crops, micro-irrigation/drip irrigation, deficit irrigation, and precision irrigation) can increase both green and blue water productivity while minimizing negative environmental impacts (Hansen 2015; Hatfield 2015; Stewart and Peterson 2015). These practices were not designed to decrease water use as such, but rather to increase yield for a given level of water use or crop water productivity. A growing literature finds evidence that the irrigation technology adoption can increase total water use (Ward and Pulido-Velazquez 2008; Pfeiffer and Lin 2014). These results call into question the capacity of irrigation efficiency improvements to address water conservation objectives.

Challenges in AWM

Although AWM is beneficial, its development may present a "wicked problem" (Brown et al. 2010). Conservation involves a large number of decisions and actors at disparate scales, and optimization in one dimension invariably leads to sacrifices in other dimensions. For example, in the extreme case of eliminating blue water impacts from irrigation, the resulting reduction in crop yield would likely lead to the conversion of grasslands or forests to agriculture to offset the reduction in overall production. Reducing tillage can conserve soil water, but also may require farmers to apply more herbicides, which may then leach to groundwater. Management practices and technologies are evolving rapidly, such as improved tillage, variable-rate seeding and irrigation, improved soil moisture probes, drones, and smartphone apps. Farmers must decide which practices will be profitable and easy to use, as well as contributing to sustainability of commodity production on their lands. Policy makers must decide how to use their political capital in the most efficient way to incentivize adoption of the most effective and least disruptive conservation measures while maintaining trust and credibility with local farmers.

AWM is a complex, value-laden endeavor, involving every aspect of farm management and the food production cycle, and requiring broad consensus to reach a sustainable use of water resources. Policies that deal with water demand for sustainable intensification of agricultural systems include a broad group of topics ranging across disciplines from plant breeding to farm and crop management (Hansen 2015). The environmental impact of AWM must also be considered, including the direct impact of irrigation on different components of the water balance and also the impact on the infrastructure associated with it (Hatfield 2015). Additionally, the HPA is threatened by contamination of groundwater and nearby surface waters due to poor water and fertilizer management (Exner et al. 2014; Juntakut et al. 2018). Agricultural pollution (fertilizer, pesticides, and salts) is a major nonpoint source contaminant and is difficult to resolve due to the constant necessity of chemical inputs for conventional agriculture (Bouwer 2000). As growing demand causes an increase in management intensity, groundwater quality will become an even greater challenge.

Conservation may appear straightforward at first glance: if irrigators pump less water, the aquifer will support irrigation withdrawals for a longer period, even indefinitely in some areas. While this concept has been recognized since the 1930s (Green 1981), not all areas with heavily impacted water resources have adopted conservation measures. This is where the interdisciplinary nature of AWM emerges. Markets, subsidies, insurance, and loans are all important in farmers' decisions, including with respect to water management and conservation. Field conditions may inhibit starting or stopping irrigation. Farmers may aim to maximize yield rather than water productivity, or resist adopting carbon and water-conserving no-till practices. When farmers succeed in supplying only enough water to support crops, salts may begin to build up in the soil, rather than flushing to deeper layers. In areas with adequate recharge, water quality is often a concern, due in part to return flow from irrigated fields. Clearly, AWM faces a major challenge of decreasing pumping rates while concurrently minimizing impacts to the agricultural sector.

One water use limitation strategy, dynamic deficit irrigation, can be a useful approach to decrease water use while minimizing the negative impacts on crop yields. With this technique, irrigation water is only applied to make up for shortfalls in precipitation, rather than being treated as the main source of water for crops (Fereres and Soriano 2007). Many studies have quantified the impact of deficit irrigation on yields, profits, and soil quality/health (e.g., Blanco-Canqui et al. 2010; Halvorson and Schlegel 2012; Kisekka et al. 2016; Schlegel et al. 2016; Manning et al. 2018), but the site-specificity of some of these results prevents them from direct extrapolation to the entire region and large-scale application (Chai et al. 2016). Moreover, the economic viability of deficit irrigation will depend on the relationship between grain price and water costs, and currently, deficit irrigation is only economically optimal within a given field season when the cost of water is already high (Manning et al. 2018). Crop insurance structuring can also deter the adoption of deficit irrigation. Thus, the many factors that affect AWM and their interactions should be evaluated to assess the best management options to secure sustainable AWM at different scales: from the farm, to the community, and entire food system.

Solutions to these AWM challenges must share some common traits. First, they must be sustainable by providing for the needs of the present without compromising future generations (Gleick 1998). Voluntary solutions must increase or maintain farmer profits; otherwise, they will not be adopted (Liu et al. 2018). Ideally, solutions will be fair and equitable among current and future users. They must be feasible for implementation (Guilfoos et al. 2016), as well as enforcement, monitoring, and evaluation; must consider risks and uncertainties; must be flexible enough to adapt to future needs; and must comply with rules and regulations for water use. In practical terms, they must be beneficial or neutral for the agricultural water cycle as a whole, rather than one-dimensional fixes that have unintended consequences. This will require assessment from multiple research disciplines.

As these challenges have escalated, so has available computational power. Many of the challenges of AWM can be addressed through modeling. Field experiments are often costly and time-consuming. Controlled variation is difficult, as is precise replication. These are the types of problems that can be addressed using computer-based experimentation in concert with field observations. Many papers (e.g., Liu et al. 2008; Laniak et al. 2013; Hamilton et al. 2015) have reviewed aspects of integrated modeling. Some of these (e.g., Barthel et al. 2012; Guzmán et al. 2018) have dealt specifically with water for agriculture. Reviews of integrated modeling generally focus on the technical and conceptual difficulties (e.g., Voinov and Shugart 2013) or the common features of many integrated modeling studies, such as stakeholder involvement (Hamilton et al. 2015). Some (e.g., Janssen et al. 2009) suggest the primacy of certain aspects of integrated modeling, such as a focus on model conceptualization and scenario development. The next section focuses on integrated modeling for AWM, including a new definition of integrated modeling.

Utility of Models for AWM

Managers of water conservation districts are creating programs to encourage water conservation in agriculture, address declining groundwater levels, and meet interstate compact obligations. Frameworks in water law can mandate simulations that describe conditions in the real world. Meanwhile, researchers and consultants often evaluate hypothetical scenarios or predict future conditions to inform district programs. These governance efforts and research teams increasingly rely on large, complex models. In the past few decades, many models have become well-developed and generated large user bases. Thus, research groups may opt to use integrated modeling as combining models can help to avoid "reinventing the wheel."

For clarity, we refer to models as mathematical representations of an empirical or process-based quantitative framework, usually accessed with computer software. We refer to individual applications of these models as "simulations," although in practice these are also often referred to as "models." For example, the Republican River Compact Model (republicanrivercompact.org), which covers parts of the HPA in Colorado, Kansas, and Nebraska, is a simulation that uses the MODFLOW groundwater model (Harbaugh et al. 2000).

Models are useful because they are simplified simulations of reality. Some models are statistical, based on observed empirical relationships. Many integrated modeling efforts, on the other hand, attempt to rely entirely on equations that govern physical processes, under the principle that empirical relationships may not hold up across the conceptual underpinnings of different models: uncertainty or variation may propagate as models are integrated. However, virtually all models, even process-based models, have some empirical components. For example, some important processes take place at a very small scale, such as transpiration occurring in a leaf, or are highly variable across short distances, such as hydraulic conductivity. For practical reasons, these parameters are usually generalized as "effective" values, rather than modeled at the scale of the process or its variability. Very large uncertainties can result from the parameterization of small-scale processes that cannot be resolved explicitly by regional models, and it is common for simulations to be run multiple times for a single model using different choices for parameters (Tebaldi and Knutti 2007). Some error is inherent in calibration and validation data. Process-based models may also contain constants that are determined through repeated experiments, such as the Von Kármán constant in fluid dynamics, used to calculate reference evapotranspiration (ET) in the FAO-56 Penman–Monteith equation (Allen et al. 1998). Ultimately, the values in process-based models have to come from measurements or estimates, and therefore, the distinction between process-based and empirical models is fuzzy.

All models involve one or more systems defined by conceptual, physical, and temporal boundaries. Models take data as inputs, perform mathematical operations meant to reflect physical processes, and generate outputs that are meant to represent real or hypothetical outcomes for the given conditions of the system. Software is used to ease translation between "the field" and "the model of the field." A model system cannot encompass every possible process; model developers must decide which processes are too complex or tangential for inclusion. The conceptual domain can vary among simulations built using the same model. For example, in a crop model such as the Decision Support System for Agrotechnology Transfer (DSSAT) (dssat.net), one simulation may assume optimal nitrogen management, while another simulation may incorporate various methods of nitrogen management in order to study or account for their effects.

Crop Simulation Models (CSMs) can be used for research information synthesis, as tools for optimizing crop system management, and for policy analyses (Boote et al. 1996). Even among this specific type of model, many options are in use. CSMs are now available for almost all major crops of the world that include but are not limited to wheat, rice, maize, potatoes, sorghum, millet, peanut, soybean, etc. Examples of models used include DSSAT (Jones et al. 2003), EPIC (Williams et al. 1989), Aquacrop (Vanuytrecht et al. 2014), SALUS (Basso et al. 2006), APSIM (Keating et al. 2003), and WOFOST (Penning de Vries et al. 1989) among many others. Models such as the Scientific Impact assessment and Modeling Platform for Advanced Crop and Ecosystem management (Enders et al. 2010) offer soil water dynamic simulations that can be combined with root development approaches and different crop water uptake mechanisms. Crop models, defined as collections of quantitative relationships, simulate the growth, development, and yield of a crop (Monteith 1996), may make it easier for users to select a combination of practices based on climatic conditions, availability of input data, and conventional water management techniques. When a researcher or team is fluent with one model, this may constitute a barrier to adoption of a new technology, including any model that is custom-built for a particular study area or research objective, even when the researcher or team decides to consider additional system components.

It is possible to integrate models when they encompass overlapping parts of the same conceptual system, so that output of one model can be used as input to another (Rotmans 2009; Voinov and Shugart 2013). Voinov and Shugart (2013) pointed out that the additional model often takes the place of data that would otherwise be used for model validation. This is often for convenience — to extend the timeframe or spatial extent of the combined model system — or for sensitivity testing, so that the effects of variation in a key parameter can be studied in a process-based framework. Thus, in this context, to decide that an integrated model is "better" than existing data means that the model outputs are available exactly when they are needed, at the desired temporal and spatial scales, and can be varied to test different scenarios. One aim of integrated modeling is to improve a simulation on a quantitative level, that is, to better describe a real system; however, validation of integrated models is particularly difficult, and is an active area of research (Voinov and Shugart 2013).

INTEGRATED MODELING

Definition and Scope

We define an integrated model as a system comprising of sequentially connected two or more models of natural and/or social systems. There is significant overlap of natural and social systems in agroecosystems, particularly with respect to producers' management decisions. Models can be integrated to a greater or lesser degree (Figure 1). Integrated models are distinct from model ensembles (USGCRP 2017), which attempt to address the uncertainties associated with a single model by aggregating outputs from multiple models of the same system(s). Each field of research in AWM has a number of existing models that can simulate various environmental and social processes. A traditional model will comprise one or more processes considered important within a specific scientific subdiscipline. Fundamentally, the purpose of model integration is to expand the complexity of the representation of a system.

The definition of integrated modeling is often vague or broad in the literature. Even some excellent case studies of integrated models frequently present their methods without explicitly defining integrated modeling (e.g., Barthel et al. 2012; Dodder et al. 2015). Hamilton et al. (2015) identified 10 dimensions of model integration, including drivers, system characteristics, and methodological aspects. Voinov and Shugart (2013) suggested that either model assembly or built-to-purpose models may be used for "integrated modeling," although they introduce the term "integral" to refer to custom interdisciplinary models created to encompass multiple systems. Liu et al. (2008) used a broad definition from the Global Water Partnership (gwp.org), which asserts that integrated modeling is any process that seeks to manage environmental resources in a sustainable manner. Some, such as Laniak et al. (2013) and Janssen et al. (2009), defined integrated modeling as a simulation tool used in the context of a broader integrated assessment. Hartkamp et al. (1999) defined integration of models as "incorporating one system into the other." A more holistic definition is given by Arnold (2013) as a network of activities undertaken by specialists in modeling methods and tools by collaborating closely with interdisciplinary teams.

Broader definitions of integrated modeling often incorporate other aspects of the modeling process or lean heavily on the concept that an "integrated" model represents multiple systems. Since systems are usually defined for convenience using disciplinary boundaries rather than boundaries that exist between processes in the real world, and all models involve representation of the real world through simplifying assumptions, it is more reasonable to refer to a single "multi-system" model as simply "a model" (or "integral model," after Voinov and Shugart 2013). If some of the model subroutines are optional, then "modular model" may be the most appropriate term (Figure 1). We take the "integrated" part of the term "integrated modeling" to refer to the integration *of models* rather than *of systems*.

One key benefit of integrated models is their use in analysis of complex functional relationships between agro-ecological characteristics and decision-making at local and regional scales (Schönhart et al. 2011; Bobojonov and Aw-Hassan 2014). When this conceptual linkage is misused, the resulting model may fail to adequately represent reality, even misrepresenting the process that the model is meant to elucidate. For example, Gisser and Sanchez (1980) developed an economic model with a highly simplified hydrologic component, assuming infinite hydraulic conductivity and a single groundwater extraction point (also known as a "bathtub model" for an aquifer). Their highly publicized conclusions, known as the Gisser and Sanchez paradox, indicated that only minimal gains are obtained from dynamically optimal groundwater management. However, more recent literature has called the Gisser and Sanchez paradox into question, using more realistic hydrologic models to show that the economic gains of management are highly contingent on the realities of the physical groundwater system (Koundouri 2004; Brozović et al. 2010; see also Case Study 1, below). In this way, integrated modeling can be a straightforward method to bring together important system features that cut across scientific disciplines.

Many models have now been integrated or are actively being developed as coupled models. DSSAT-RZWQM (Ma et al. 2008), WOFOST-SWAP (Van Walsum 2011), DSSAT-SWAP (Dokoohaki et al. 2016), and Soil and Water Assessment Tool (SWAT)-MODFLOW (Bailey et al. 2016) have been applied to problems related to AWM. The coupling approaches have ranged from external linkage where input and output data were treated separately rather than using a computer algorithm, to using code wrapping, essentially bringing one model into another as a module. Several platforms like OMS3, Python, and the

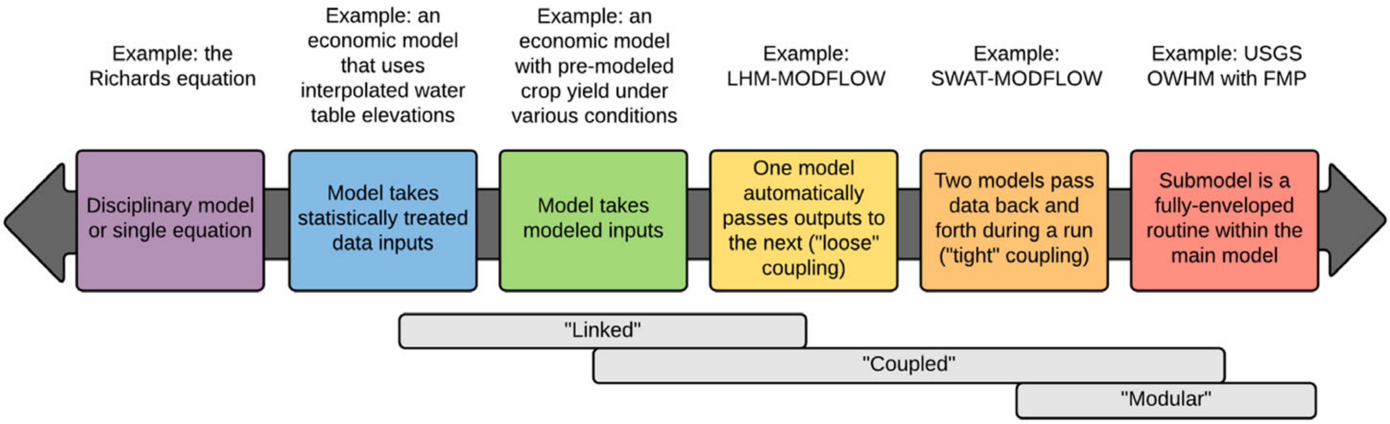

FIGURE 1. An integrated modeling continuum. Most models are not designed for integration; if they are designed for integration, they are typically modular. Large interdisciplinary projects often use linked or coupled models, close to the center of the continuum, which increase flexibility and take advantage of built-in user bases, but present challenges for software in addition to conceptualization of the combined system. Models anywhere on the continuum may be process-based, empirical, or a combination of the two. LHM, Landscape Hydrology Model; SWAT, Soil and Water Assessment Tool; USGS, United States Geological Survey; OWHM, One Water Hydrologic Flow Model; FMP, Farm Processes Model.

Ensemble Kalman Filter method have been used to achieve integration/coupling of models.

As the in-field evaluation of every water management option is not possible in the space and time scales necessary for agricultural water managers to make an informed decision, the integration of SOC models together with crop and groundwater models can be very beneficial. Some of these models focus on supporting processes of soils such as water (fluxes through soil profile) and nutrient (N, C, P) cycling. For example, the CENTURY/DAYCENT model (Parton et al. 1988, 1998) focuses on carbon and nutrient dynamics and has been widely accepted by the ecological and geochemical communities, though they do not use physically based equations to calculate data. The HYDRUS 1D model (Šimnek et al. 2008, 2016), which simulates water flow in soils using Richard's equation, has been widely used. It has been integrated with various root growth models (Groenendyk et al. 2012; Peña-Haro et al. 2012; Zhou et al. 2012; Li et al. 2014; Han et al. 2015; Hartmann et al. 2018). Liang et al. (2016) developed an integrated soil-crop system model called Soil Water Heat Carbon Nitrogen Simulator, containing modules to model soil water, soil temperature, soil carbon, soil nitrogen, and crop growth in North China. A DSSAT-HYDRUS 1D coupling was tested to simulate soil water dynamics along with crop growth and yield in Florida, USA (Shelia et al. 2018). Since both DSSAT and HYDRUS 1D are written in FORTRAN, their source codes were modified so that both the models could "talk" to each other, a process which is becoming easier as code is modularized.

Over the past few decades, geographic information systems (GIS) have emerged as powerful tools to understand and solve problems over a defined space by providing visualization and spatial analysis capacities. Agriculture, as a spatial activity, has benefitted from the use of GIS. Spatial modeling techniques like reclassification, overlay, and interpolation (Yakuup 1993) can be helpful in analyzing agronomic or crop processes and their variation at spatial and temporal scales. Numerous studies have reported on integration of GIS with various model interfaces that vary by interface type, data format (raster/vector), and spatial reference (WOFOST-ArcInfo, Van Lanen et al. 1992; DSSAT-ArcInfo, Luijten and Jones 1997; DSSAT-IDRIS, Thornton et al. 1997; DSSAT-ArcInfo, Ines et al. 2002). The strategy to interface models with GIS depends on the purpose of the application and the factors that govern these strategies, including format and structure of data, complexity of physical processes being simulated, scale, and relation between modeled runs and modeled fields (spatial units) (Hartkamp et al. 1999). There is a tremendous scope of application of site-specific models like crop models in risk assessment, climate change/variability impacts, policy making, and productivity analysis by combining their strengths with capabilities of GIS.

To help guide the decision-making process on water conservation strategies under different scenarios of climate change, modelers have integrated the output from dynamically downscaled global climate model (GCM) data to a regional scale for a future period of time to determine the range of hydrologic possibilities that could be expected for their particular areas of study. These results can highlight the potential need for conservation strategies in water-limited regions. Using downscaled data as a key component in integrated modeling has become popular since the introduction of large-scale climate modeling projects such as Coupled Model Intercomparison Project Phase 5 (CMIP5) (Hayhoe et al. 2017). For example, multi-model ensembles of Regional Climate Models (RCMs) have been used to drive the Variable Infiltration Capacity model to examine projected hydrological changes in the Southwestern U.S. (Pagán et al. 2016). Other researchers have used RCM output to drive crop simulations in central Asia (Bobojonov and Aw-Hassan 2014) and the Midwestern U.S. (Glotter et al. 2014) to examine the agronomic response to changes in regional climate. Researchers have developed crop models to operate at large spatial scales integrated with land surface components of GCM (HadAM3) and to simulate seasonal growth of a summer annual crop (Osborne et al. 2007).

Integrated models are often used specifically to evaluate linkages and sensitivities between systems that are traditionally studied independently and sometimes in different scientific disciplines. For example, the Community Climate System Model, first released in 1996, has been developed into a sophisticated integrated model that consists of atmosphere, land, ocean, and sea ice components that communicates information on both state and fluxes (Gent et al. 2011). The exchange of information across the surface and time integration of the system are controlled by a coupler, providing the central point of control for dealing with important scientific requirements in the model, such as energy conservation and variable time steps between models (Robert et al. 2005). This integrated model is one of many models that were used in the CMIP5. The CMIP5 was an internationally coordinated effort to examine the mechanisms responsible for poorly understood feedbacks with the carbon cycle and clouds; climate "predictability" and the predictive power of models on decadal time scales; and the variability produced by models forced to simulate similar conditions (Taylor et al. 2012). In the short term, these climate models contain many features that seem unrelated to AWM, but in fact may exert a controlling influence on agriculture in the High Plains; for example, these models may indicate whether dryland farming will become riskier in the next several decades, and thus influence the future value of groundwater in the HPA.

Challenges for Integrated Modeling

Model integration can present several challenges, some technical and others conceptual (Voinov and Shugart 2013; Hamilton et al. 2015). In earth sciences, models are rarely developed with coupling in mind, which can lead to considerable time and resource investments for integration (Robert et al. 2005; Liu et al. 2008). All of the challenges that apply to a single model are also applicable to integrated models. According to Pearson et al. (2011), integrated models may not escape the concerns of conceptual linkage between biophysical and social processes, and may also miss important threshold values ("tipping points") for physical parameters. Research teams often underestimate the challenges of model integration (Liu et al. 2008; Janssen et al. 2009).

Technical challenges result from models being written in different computer languages (e.g., MATLAB, FORTRAN, Python) and their dependence on "legacy code" (Liang et al. 2016), which may no longer be supported by model creators. Some computer languages and source codes are proprietary and/or must be compiled prior to running, or may require extensive setup in an additional software application. Regardless of the language, access to model source code is generally needed for tight coupling of models (Figure 1), and someone on the team must be knowledgeable enough to reformat intermediary datasets between models and coax downstream models into accepting them. Individual models are often poorly documented because documentation is challenging, may seem unnecessary, and is poorly rewarded in traditional academic settings. The documentation for a single instance of a model may be hundreds of pages long (e.g., Deeds and Jigmond 2015). Acquiring the requisite programming and software expertise may also come at the expense of disciplinary depth.

When models are integrated by formatting the output of one model to serve as the input of another model, this can be done uni- or bidirectionally; also, information may pass from one model to another during the model run, or models may be run in sequence. Conceptually, models must have parameters in common in order to be integrated, so that the models can "talk" to one another. These parameters must be scaled harmoniously in space and time in addition to formatting requirements. Janssen et al. (2009) and Voinov and Shugart (2013) also noted the challenge of ensuring a shared conceptual framework across all integrated models. For example, when integrating the MODFLOW groundwater model (Langevin et al. 2017) with a surface hydrology model such as SWAT (Arnold et al. 1998; Neitsch et al. 2011) or Landscape Hydrology Model (Kendall 2009), it is vital to ensure that critical processes such as ET are not duplicated or handled incongruously. Without sufficient knowledge of model interfaces and input requirements model integration can create misleading results. Greater data availability can facilitate model integration but also presents its own set of challenges.

Often models are built to incorporate "big data," such as datasets comprising hundreds of climate reanalysis rasters, thousands of yield observations, or millions of well records. Big data can test the limitations of software and computer memory. Model outputs are often large files, leading to difficulties in digesting and storing results. This challenge is often multiplied in integrated models, which may be more complex than the sum of their parts. The computing power required of certain models, such as the Weather Research and Forecasting (WRF) climate model, generally necessitates the use of high-performance computing systems or supercomputers. Supercomputers are subject to downtime for maintenance, instability, and runtime limitations. Advances in overall computing power will help but will also enable greater complexity in data assimilation and modeling, leading to the potential of the problem scaling along with its purported solution.

Hardware can also impose a time limitation: model runs can take anywhere from seconds to months. Longer model runs become necessary as model complexity increases, but as the length of an individual run increases, the time necessary for parameter estimation or sensitivity testing increases multiplicatively. When running some models such as climate model simulations, the parameter choices can also differ in their level of complexity (Okalebo et al. 2016), which can drastically affect run time. AWM research is increasingly using dynamical downscaling of GCM data, which can take on the order of days to weeks depending on the computing resources available, the experimental design, size and resolution of the domain, and the length of the simulation period. Because of the large number of GCMs available and the time constraints of each downscaled simulation, researchers are faced with the dilemma of choosing a subset of models that produce “realistic” conditions for the evaluation of a historical period or choosing the entire available ensemble of GCMs to assess the full range of climatic uncertainties. High-performance computing can assist but requires additional expertise and access.

Models are sometimes integrated specifically to derive input to a sequentially linked model. For example, a complex process-based crop model may incorporate a simple empirical model to estimate solar radiation. Nevertheless, integrated models on the whole have the same data availability challenges as other models. Some types of data are difficult to collect, or highly heterogeneous and thus difficult to scale up from the point of measurement. Examples include hydraulic conductivity, ET, and individuals’ attitudes toward conservation. Often data are collected at a point, but is needed for a larger area, such as precipitation from rain gages. Some data are widely available, but can be difficult to process or interpret, such as LANDSAT imagery (Deines et al. 2017) or social media mentions (Zipper 2018). Compounding these challenges, different locations often have different data availability, but similar modeling needs.

Some integrated modeling challenges are conceptual as well as technical. Scale is a constant concern in integrated modeling. Most AWM models either cannot capture variation in water applied at a subfield scale or do not cover an area large enough to be relevant for public policy. Rapid innovation at multiple scales limits the capacity of AWM models to reflect current practice. Meanwhile, most existing models are created with an expectation that they will be used at a particular scale, which may or may not be similar to models in other fields of study. Sensitivity testing is particularly vital for integrated models, which are frequently employed with the intention of investigating sensitivities in real systems (e.g., Dodder et al. 2015) without any method of validating the resulting sensitivity estimates.

Other challenges arise when the understanding of processes is limited — one of the driving forces for the development of models in the first place. Though most chemical, physical, and biological processes are well documented, the microbial component of soil, for example, remains a black box in many AWM models, particularly when it comes to microbial kinetics and dynamics due to soil environmental changes. Further research must focus on how to effectively incorporate soil properties taken at a small scale and incorporate data at a larger scale such as entire watersheds and landscapes. Other fields also face difficulties in mathematically describing important processes, such as the role of trust and leadership in water conservation. These processes need to be integrated into models used to evaluate water management scenarios.

Case Study 1: Incorporating Complexity through Integrated Modeling

The HPA is one of the largest and most heavily utilized aquifers in the world, supplying roughly 30% of all irrigation water for the continental U.S. (Dennehy et al. 2002). Concerns with declining water tables in Texas in the 1930s eventually led to the call for efficient agricultural water use throughout the High Plains region (White et al. 1946; Green 1981). Despite widespread declines, particularly in the Southern and Central High Plains, the aquifer remains an important source of groundwater: Fenichel et al. (2016) estimated that from 1996 to 2005, irrigators in Kansas withdrew groundwater valued at about \$110 million/yr in natural capital. Research from the HPA may be applicable to other large aquifers such as the Loess Plateau of China (Gates et al.

2011) and the Murray–Darling Basin of Australia (Quiggin et al. 2010).

A decrease in water pumping for irrigation in some areas of the HPA is imperative to prolong or sustain its use. Steward et al. (2013) calculated that a reduction of current pumping by 80% will be necessary to approach natural recharge in the Kansas portion of the aquifer, while Whittemore et al. (2016) estimated that a pumping reduction of 36% would suffice to stabilize the water table in most of the Kansas High Plains. Large reductions in pumping will impact agricultural production, leading to changes in management practices, yields, or both. This is problematic considering that in the near term, low commodity prices and high input costs encourage farmers to irrigate for maximum yields, while in the next several decades, demand for agricultural products is expected to increase globally (Bouwer 2000). According to Hansen (2015), securing global food production requires securing water resources for irrigated agriculture. Despite continual increases in agricultural water use efficiency, recent research suggests that additional water savings (up to and beyond 20%) can be achieved without negatively impacting cash returns, for example, growing crops that need less water or focusing irrigation on particular stages of plant development (Golden and Liebsch 2017). AWM can stave off or ameliorate the effects of water resource depletion.

Water scarcity concerns (Figure 2) have led approximately 50 local areas in the HPA to organize into irrigation management districts, beginning in the 1950s in Texas. While some of these areas have avoided implementing policies that directly regulate water use, many are beginning to place restrictions to mandate conservation. For example, 11 of 23 Nebraska Natural Resources Districts have implemented irrigation flow allocations as of October 2017 (Upper Big Blue Natural Resources District 2017). In Kansas, the state government implemented a subsidy program to encourage the adoption of more efficient, low pressure irrigation systems (Pfeiffer and Lin 2014). Integrated and traditional modeling studies in the HPA have informed these policy-making efforts.

The importance and vulnerability of the HPA have catalyzed an exceptional amount of research investigating strategies for AWM, including some pioneering instances of integrated modeling for AWM such as the Coupled Hydrologic Systems (COHYST) simulation of the Platte River Corridor in Nebraska (Cannia et al. 2006). COHYST was established as a single-discipline (MODFLOW groundwater) simulation, followed in recent years by the integration of the original groundwater modeling framework with models for crop growth and surface hydrology.

Water management groups across the HPA seek strategies to reduce the rate of groundwater decline while minimizing impacts on producer profitability. Integrated modeling can help to evaluate strategies for conservation and agricultural profit. Groundwater scarcity and a growing interest in collectively pursuing AWM catalyzed producers in the Republican River Basin of Colorado to form the Water Preservation Partnership (WPP). The WPP consists of representatives from each of the Basin's eight Groundwater Management Districts (GWMD) as well as other regional natural resource authorities. The WPP aimed to encourage conservation but determined that more information on the effects of conservation was necessary to build consensus among the Basin's groundwater stakeholders. Specifically, the WPP wanted to understand the costs and benefits of several groundwater management policies under consideration. To address this information gap, the WPP began collaborating with researchers at Colorado State University (CSU) to better understand the costs and benefits of conservation policy implementation.

The integrated modeling framework combined a custom-built economic model, an agronomic model (Aquacrop), and a MODFLOW simulation, as described in Hrozencik et al. (2017). The resulting simulations leverage the expertise of the stakeholder group with insights of the research team to understand the costs and benefits of groundwater conservation policies. Model results were shared with the larger community of groundwater users in the Basin through a public report as well as a series of informational meetings held with local GWMDs. GWMDs in the Basin have used the information provided by the integrated modeling effort to make the case for conservation to their constituents. To date, one of the Basin's GWMDs has acted on the model results and enacted a resolution to reduce groundwater use by 20%.

This example of an integrated hydro-economic model demonstrates the sensitivity of agro-economic systems to physical constraints, and vice versa. Any single disciplinary model — economic, agronomic, or hydrologic — would traditionally minimize components involving other disciplines, and would thereby miss the features that determine the future of irrigation in the region. In this case, model integration provided a more holistic picture of the interactions between yield, profit, and resources.

Case Study 2: Simulating Hydrologic Impacts of Irrigation

Many parts of the U.S. experience large variations in surface and soil water availability due to seasonal evaporative demand and stochastic upstream precipitation. This variability is translated to crop irrigation

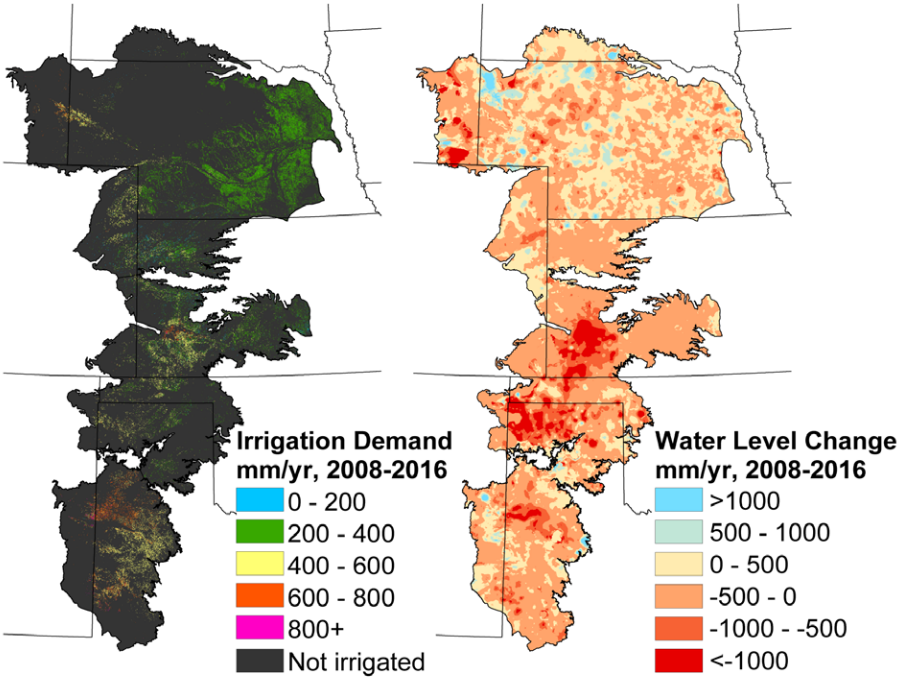

FIGURE 2. Average estimated irrigation demand and water level change for the High Plains Aquifer, 2008–2016. Methods and data sources for irrigation demand map are in Supporting Information. Water level change: methods from Haacker et al. (2016). Aquifer boundary from Qi (2009). Crops identified using USDA National Agricultural Statistics Service Cropland Data Layer (2008–2016).

demand, which also depends on factors like interannual and intra-seasonal changes in precipitation, evaporative losses, and crop growth stage.

McNider et al. (2015) demonstrated the coupling of a crop model (DSSAT) with a hydrologic model Water Supply Stress Index (WaSSI) to be used as a decision support tool to determine when and where an excessive withdrawal is made for irrigation use. The GriDSSAT is a gridded version of the DSSAT-CSM, which can therefore accommodate simulations over a larger area. The model is used to calculate water requirements for a particular crop, and the irrigation water withdrawal data is fed to the hydrologic model to determine the extent to which the irrigation demand can be met by the surface water available in the watershed. Thus, water stress levels associated with different crops, climate, and agricultural management plans can be determined for a region.

GriDSSAT and WaSSI are coupled at temporal scales covering long-term historical simulations as well as real-time short term. In the long-term mode, the coupled model was used to calculate limits on expanded irrigation at a regional spatial scale in the Southeastern U.S. While the Southeastern U.S. has not historically faced water scarcity, it is vulnerable to climate change, and its crops are unlikely to be resilient to variable precipitation and drought. In addition, blue water resources are used intensively for irrigation along the Mississippi River, for crops such as cotton and rice. The coupled GriDSSAT-WaSSI can help answer the question of how much area can be irrigated under past or future climates without jeopardizing environmental flows. In the real-time short-term mode, the GriDSSAT can simulate the status of crop stress due to environmental factors, contribute toward drought declarations, and support risk assessment for yield and drought losses. The GriDSSAT-WaSSI system can be used to provide information regarding the capability of the hydrology of the basin to be able to support irrigation as well as anthropogenic demands and may offer a decision support tool to impose intermittent water withdrawal restrictions.

The example of GriDSSAT and WaSSI shows that challenges for integrated modeling can be overcome to create a useful, practical tool for AWM. However, even when integrated models are used to create successful simulations, transferring the integrated model to a new study area can require revisiting the conceptual basis for individual model components.

DISCUSSION

Integrated modeling approaches inherently acknowledge that AWM does not take place in a vacuum and conservation is often driven by combined agronomic, social, political, and economic forces (Smidt et al. 2016). Models that attempt to isolate just a few processes within AWM run the risk of not being applicable in the real world. Integrated modeling can also allow testing of far-flung effects among processes, like the effect of streamflow depletion on farm profitability. Since real systems fail to reflect disciplinary boundaries, this has a great potential to improve decision-making. It is generally more convenient and efficient for researchers, and less expensive for management and funding agencies, to integrate models rather than starting from scratch. However, representing interrelated processes through integrated modeling is not inherently better than representing those processes through a single built-for-purpose interdisciplinary model.

Feedbacks between crop, water, and soil processes are one example of an area for future research in integrated modeling. Soil water processes, soil health, and spatial soil variability (Sharda et al. 2017) are critical components in crop growth models and an essential component of most integrated models for AWM. Vereecken et al. (2016) reviewed these types of soil modeling options, their role in the evaluation of ecosystem services, and the challenges associated with them. They stressed the importance of integrating soil models into other disciplines. Thus, AWM's effect on soil health and the outcome of soil health in relation to water use efficiency (Cano et al. 2018) should be integrated into modeling approaches. As a result of the small scales at which soil processes operate, and the difficulty in assessing chemical and biological pathways, soil is often neglected in agricultural modeling. As has been done in previous work on the Great Plains region (e.g., Paustian et al. 1995; Robertson et al. 2017), the integration of these models will allow consideration of not only the effect of management but also the impact of climate change.

Agricultural sustainability begins with soil health, but it does not end there. These applications of integrated modeling provide evidence that integrated models can have advantages over other tools. One of the greatest advantages of using integrated modeling is the ability to incorporate additional models in lieu of simplifying assumptions. For example, traditional economic models for AWM often assume that the effects of drawdown from one well are instantly transferred to all other wells in the area. Similarly, hydrogeologic models often make unrealistic assumptions about irrigation scheduling or the impact of depletion on pumping decisions. Hydro-economic models can improve the conceptual foundation of complex systems (Hrozencik et al. 2017; Foster et al. 2014).

Integrated modeling is a way of addressing the fundamental tension between modeling as a reductive process and AWM as a holistic process. Integrated models can provide more informed answers to some dilemmas in AWM, but like any tool, they must be used with the end in mind. They are not appropriate for addressing every question, and integrated modeling in itself is just one of many tools that are necessary to address long-term sustainability and resilience of irrigated agricultural systems. Models are extremely useful — they are the only quantitative method for examining counterfactuals or predicting future conditions under different scenarios. To remain relevant, integrated models should be designed while keeping in mind the imperatives of AWM, and the challenges that are of greatest concern to producers and policy makers. Some of these concerns are difficult to model, such as risk, profitability, and extreme events. Nevertheless, researchers should do their best to incorporate the dimensions of AWM with the greatest potential for sustainable water savings, and to ensure that models are up-to-date with current farming praxis.

Three conditions must apply for integrated modeling to solve problems in AWM (Figure 3). First, sufficient input and calibration and validation data must be available. Second, the research question should require consideration of a complex system with interdependency between processes traditionally studied as parts of different disciplines, such as economics and hydrology. And third, models must exist which together can cover important processes to answer the research question and enables conceptual combination of the models. When models are used for applied problems like AWM, whether integrated or not, they should be designed in a way to be useful to managers, farmers, and/or policy makers, either directly through user interfaces, i.e., decision support tools, or through generation of useful outputs. To do this well, the process of integrated modeling requires many of the other characteristics commonly associated with integrated modeling, such as stakeholder involvement and careful scenario development (Janssen et al. 2009; Hamilton et al. 2015).

Integrated model development for AWM is generally driven by a desire to represent a real system, suggesting the primacy of practical applications for these models. Indeed, integrated models can improve forecasting, "test" the effects of interventions prior to expensive field trials or policy implementation, and can compensate for the fact that management takes place over many orders of magnitude of spatial and temporal scales. However, in order to be useful, simulations that use integrated (or custom-built interdisciplinary) models must have conceptual models that incorporate the latest technologies and

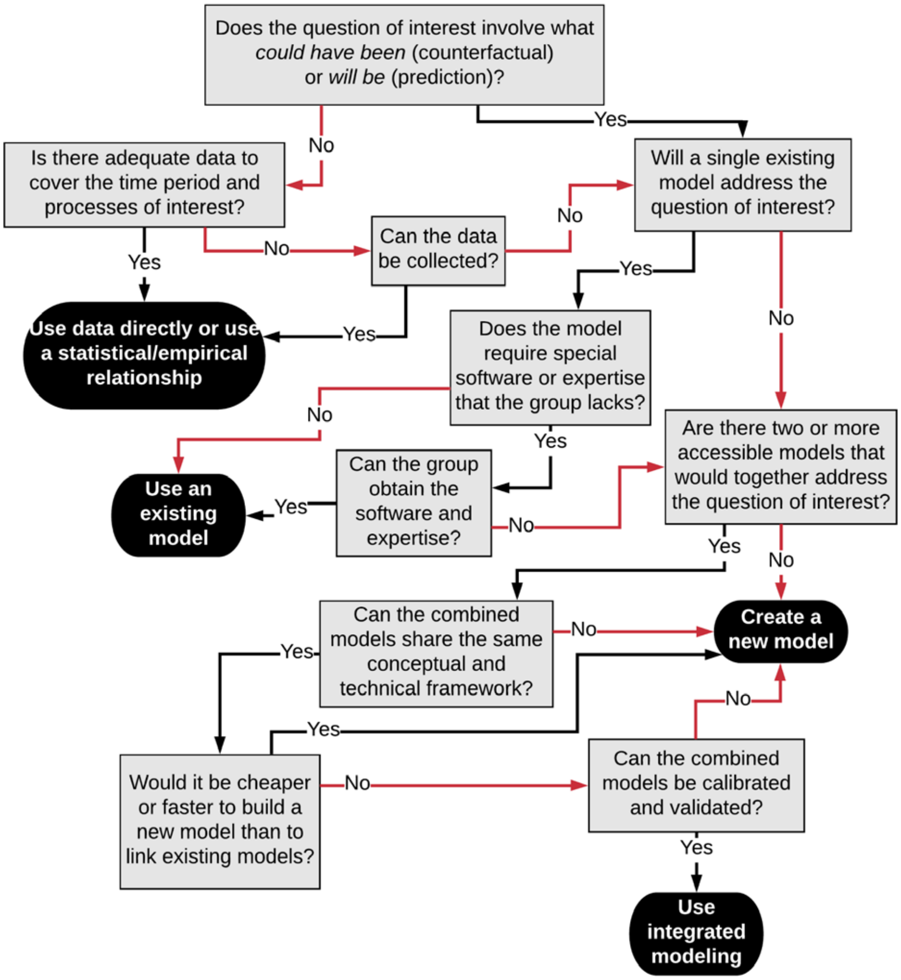

FIGURE 3. Flowchart to decide whether integrated modeling is the most appropriate approach to a research problem in environmental science and management.

practices for farm management, appropriate scenarios that are developed in tandem with stakeholders (Liu et al. 2008; Janssen et al. 2009), and outputs that are formatted for effective dissemination. In some cases, an integrated model is meant to be used as a decision support tool. In those instances, it is vital that the user interface is intuitive and easily accessible. This can be difficult, particularly because the development of user interfaces is beyond the scope of traditional scientific disciplines and involves as much art as science. At the end of a research project, it may be tempting to leave the model user interface (along with documentation) for future work, but this hobbles the utility of scientific advances.

On the other hand, model integration should only be considered after simpler approaches are ruled out. When there is limited data or a simple system, a custom-built statistical model may perform better and be easily validated. If one existing model covers the system of interest, it should be considered, even if no one on the research team is an expert in that model. Difficulties with scale may also suppress certain models from being coupled at least in certain directions. For example, WRF, a regional-scale climate model, is typically initialized with data on a coarse latitude and longitude resolution to generate model output on a local to regional scale, whereas most widely used crop models, such as DSSAT, AquaCrop, and SALUS, operate at a scale of one square meter. While it may be a good idea to use outputs from WRF in DSSAT, it would be decidedly challenging to amalgamate enough simulations in DSSAT to create a useful input for WRF. Finally, in some cases, farmers have innovated in ways that are not easily incorporated into models. For example, variable-rate irrigation is becoming more common in the High Plains, but it is conceptually challenging to vary water application inputs across a few meters within a regional-scale model.

CONCLUSIONS

As H.L. Mencken said, "For every complex problem, there is an answer that is clear, simple, and wrong." If the answers for AWM that arise from integrated modeling are clear and simple, it is probably a result of the failure of models to encompass the entire complexity associated with the agricultural water cycle. Or, researchers may not recognize barriers to adoption (e.g., crop insurance, labor costs, tradition) that seem foreign to physical scientists in particular but are imperative to agricultural producers. The rise of interdisciplinary science in coupled human and natural systems catalyzed the integration of models across traditional scientific domains to address pressing research questions. However, model integration comes with its own challenges particularly as farm water management becomes more complicated. Thus, the technical and conceptual capacity of models must keep pace with water manager needs and incorporate the rapidly expanding irrigation management options.

According to one of the High Plains producers whose land straddles the Texas–Oklahoma state lines, some of the prevailing management practices are innovating ahead of university researchers (Darren Buck, 2018, personal communication). Integrated modeling can be a step in the right direction, but it is necessary for researchers to use the modeling as a means of escaping their research silos rather than remaining within their disciplines by continuing to focus exclusively on the model components that fall within their own domains. Many agricultural producers recognize the need for researchers to engage with practitioners. Integrated modeling, like modeling in general, remains just one tool in an arsenal of approaches to AWM.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: Methods for Figure 2, irrigation demand for the High Plains Aquifer.

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