8-5-2019

Modeling irrigation behavior in groundwater systems

Timothy Foster
Imperial College London, timothy.foster10@imperial.ac.uk

Nicholas Brozovic
University of Illinois at Urbana-Champaign & University of Nebraska- Lincoln, nbrozovic2@unl.edu

Adrian P. Butler
Imperial College London

AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2014WR015620

Key Points:

- Declining well yields restrict optimal irrigated area and irrigation demand
- Reductions in irrigated area are required to avoid damaging crop water stress
- Failure to model well yield leads to overprediction of profits and resilience

Correspondence to:
T. Foster,
timothy.foster10@imperial.ac.uk

Citation:
Foster, T., N. Brozović, and A. P. Butler (2014), Modeling irrigation behavior in groundwater systems, *Water Resour. Res.*, *50*, 6370–6389, doi:10.1002/2014WR015620.

Received 25 MAR 2014
Accepted 9 JUL 2014
Accepted article online 12 JUL 2014
Published online 5 AUG 2014

Modeling irrigation behavior in groundwater systems

Timothy Foster[1], Nicholas Brozović[2,3], and Adrian P. Butler[1]

[1]Department of Civil and Environmental Engineering, Imperial College London, London, UK, [2]Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, Illinois, USA, [3]Robert B. Daugherty Water for Food Institute, University of Nebraska, Lincoln, Nebraska, USA

Abstract Integrated hydro-economic models have been widely applied to water management problems in regions of intensive groundwater-fed irrigation. However, policy interpretations may be limited as most existing models do not explicitly consider two important aspects of observed irrigation decision making, namely the limits on instantaneous irrigation rates imposed by well yield and the intraseasonal structure of irrigation planning. We develop a new modeling approach for determining irrigation demand that is based on observed farmer behavior and captures the impacts on production and water use of both well yield and climate. Through a case study of irrigated corn production in the Texas High Plains region of the United States we predict optimal irrigation strategies under variable levels of groundwater supply, and assess the limits of existing models for predicting land and groundwater use decisions by farmers. Our results show that irrigation behavior exhibits complex nonlinear responses to changes in groundwater availability. Declining well yields induce large reductions in the optimal size of irrigated area and irrigation use as constraints on instantaneous application rates limit the ability to maintain sufficient soil moisture to avoid negative impacts on crop yield. We demonstrate that this important behavioral response to limited groundwater availability is not captured by existing modeling approaches, which therefore may be unreliable predictors of irrigation demand, agricultural profitability, and resilience to climate change and aquifer depletion.

1. Introduction

In many semiarid and arid regions groundwater plays a critical role in maintaining agricultural productivity and food security, buffering farmers against climate change and variability. However, the intensive levels of abstraction for irrigation have severely depleted many of the world's major aquifers leading to concerns about the long-term sustainability of groundwater-fed irrigated agriculture [*Rodell et al.*, 2009; *Gleeson et al.*, 2012; *Scanlon et al.*, 2012; *Wada et al.*, 2012; *Steward et al.*, 2013]. In addition, future climate change and population growth are expected to exacerbate existing depletion through increases in water demand [*Sauer et al.*, 2010; *Brown et al.*, 2013] and shifts in the spatial and temporal availability of water [*Elliott et al.*, 2013; *Schewe et al.*, 2013].

Integrated hydro-economic analyses are valuable tools for policy development in coupled human-water systems. These models have been applied to a diverse range of water management issues [*Harou et al.*, 2009], including the assessment of policy solutions to groundwater depletion problems in regions of intensive irrigation [*Schoups et al.*, 2006; *Harou and Lund*, 2008; *Maneta et al.*, 2009; *Brozović et al.*, 2010; *Bulatewicz et al.*, 2010; *Varela-Ortega et al.*, 2011; *Steward et al.*, 2013]. The reliability of integrated modeling as a tool for improving water management is, however, dependent on the ability of models to capture the structure and variables which govern observed water user decisions. In this paper we seek to advance current representations of optimal water use decision making for use in integrated models, focusing on methods used to predict agricultural water demand. The major contribution of this study is the development of a model of irrigation decision making that incorporates explicitly the biophysical and hydrogeological parameters that control farmers' actual field-level groundwater use choices, but which are often neglected in existing representations of agricultural water demand in integrated hydro-economic models.

The link between the agricultural production and hydrological systems in integrated hydro-economic models is the crop-water production function. Crop-water production functions used in hydro-economic models commonly describe crop yield returns to total seasonal irrigation inputs. These functions may be derived from evapotranspiration models [*Doorenbos and Kassam*, 1979], through the fitting of nonlinear functions to field-level observation data [*Cai and Wang*, 2006], or from biophysical crop simulation models. As data on crop yield response to irrigation are often sparse, crop simulation models are increasingly being employed as state-of-the art tools to model the crop-water production function. Notably, the ability of crop models to generate large quantities of high quality water-limited yield data has enabled researchers to extend the seasonal crop-water production function to account for the production uncertainty introduced by interannual weather variability [*Brumbelow and Georgakakos*, 2007; *Geerts et al*., 2009; *Schütze and Schmitz*, 2010; *García-Vila and Fereres*, 2012; *Kloss et al*., 2012]. Resulting stochastic crop-water production functions offer advantages over traditional aggregate empirical models, for example when seeking to model the impact of risk preferences on irrigation demand.

However, despite modeling advances, the value of existing production functions in modeling coupled human-water systems remains limited due to the mismatch between the variables used to define the production function and those which govern actual irrigation decision making. First, irrigation scheduling is an intraseasonal decision problem. The choices of when to irrigate and how much water to apply are commonly driven by target soil moisture levels during the growing season designed to minimize crop yield losses [*Jones*, 2004]. This assertion is supported by evidence indicating the adoption of soil moisture measurement technologies in agricultural production [*National Agricultural Statistics Service*, 2008], along with the use of soil moisture content as a key decision variable in computational models used to inform farm water management and irrigation scheduling [*Smith*, 1992; *Clark and Rogers*, 2002; *Steduto et al*., 2009]. Contrastingly, predictions of agricultural water demand in integrated hydro-economic models are based on crop-water production functions formulated in terms of total seasonal applied irrigation. These functions therefore have limited relevance to actual irrigation planning, and as a result may potentially provide unreliable predictions of agricultural production and water use decisions. In this study we develop an alternate intraseasonal formulation of the crop-water production function. Specifically, we generate predictions of the functional relationships between the level of soil moisture depletion, daily irrigation decisions, and crop yield in order to model appropriately the irrigation decisions made by farmers. The basis for our behavioral model is the biophysical crop simulation model, AquaCrop [*Steduto et al*., 2009].

In addition, groundwater-fed systems impose unique constraints on irrigation decision making that are also not accounted for by existing crop-water production functions. Well yield, for example, places an upper limit on the rate at which water may be pumped out of an aquifer and applied to a cropped field as irrigation. Consequently, declines in well yield have been shown anecdotally and empirically to affect farmer irrigation behavior and to reduce crop production returns due to the constraints that low well yields impose on instantaneous irrigation application rates [O'*Brien et al*., 2001; *Peterson and Ding*, 2005; Lamm et al., 2007; *Colaizzi et al*., 2009; *Wines*, 2013]. Aquifer depletion reduces the available depth of saturated thickness causing a nonlinear reduction in well yield to avoid well dewatering during pumping. Limited well yields may also be caused by other factors such as geological constraints that naturally cap the abstraction potential from certain aquifers or due to poor maintenance of pumping equipment. However, despite the apparent importance of well yield as a constraint on groundwater-fed irrigation, current frameworks for simulation modeling of the crop-water production function do not consider the impact of limited instantaneous application rates on crop production. As a result, in situations where well yield is restricted, existing models that do not explicitly account for such constraints may be poor predictors of the irrigation decision making by farmers. Therefore, in this study we model the variability in intraseasonal crop-water production functions induced not only by weather variability, but also by changes in instantaneous application rates dependent on well yield and the area over which irrigation water is applied.

We couple the developed stochastic intraseasonal crop-water production function to a field-level economic model that represents a farmer's decision making in terms of land and water use choices. The farmer is assumed to maximize utility with respect to the choice of irrigated area, reflecting the fact that irrigated area must generally be fixed preseason given available well pumping capacity and subject to uncertainty about future conditions during the growing season. This contrasts with many existing studies [*English*, 1990; *English et al*., 2002; *Evans and Sadler*, 2008; *Geerts and Raes*, 2009; *Wang and Nair*, 2013], which solely focus on the importance of optimization of per-area irrigation intensity (e.g., deficit irrigation) as an adaptation to reduced water supply. One approach that has considered the trade-offs between deficit irrigation and irrigated area adjustment is the approach proposed by *Rosegrant et al*. [2002]. The authors propose that a farmer will switch from deficit irrigation to adjusting irrigated area once water supply drops below the level necessary to meet a specified proportional threshold of total seasonal crop evapotranspiration demands. Furthermore, their model also considers crop yield to be negatively affected by monthly water deficits that occur within growing season. However despite this, the ability of the model of *Rosegrant et al*. [2002] to evaluate the impacts of intraseasonal groundwater supply restrictions imposed specifically by well yield may be limited for two reasons. First, well yield restricts irrigation supply at a daily time scale potentially leading to different predictions of final crop yield than those obtained when considering the effects of lumped monthly water deficits. Second, intraseasonal water supply restrictions may affect not only crop yield but also irrigated area as the maximum irrigation depth that can be applied each day is a function of both well yield and the area the farmer chooses to irrigate. As a result, we hypothesize that by matching the structure of modeled and observed decision making in terms of irrigated area and by fully accounting for the daily supply constraints imposed by well yield, our model, building on the approach of *Rosegrant et al*. [2002], will enable more complex trade-offs between intensive (i.e., per-area irrigation intensity) and extensive (i.e., irrigated area) margin adjustments to emerge.

The coupled model is applied to an example of irrigated corn production in the Texas High Plains region of the United States, where irrigated agriculture is both a key part of the rural economy and a major driver of declining groundwater resources [*Colaizzi et al*., 2009]. The aims of the analysis are to assess changes in farm-level irrigation behavior, profitability, and production risk in response to groundwater supply restrictions. We compare the results given by our model with those obtained when using existing formulations of the crop-water production function in order to examine the limitations of current production functions for predicting optimal agricultural land and groundwater use decisions. Subsequently, we outline potential areas for model improvement and how future work could upscale our field-level modeling framework to inform the development of robust aquifer-scale policy solutions to tackle competing goals of groundwater and food security.

2. Methodology

This section discusses the methodological steps used to predict optimal irrigation decision making under groundwater supply constraints. In section 2.1 the crop simulation model used in this study is introduced. Section 2.2 then details how this simulation model is applied to generate stochastic intraseasonal crop-water production functions, and contrasts these with existing production functions used to model irrigation decision making. Finally, section 2.3 describes the methodology to apply the developed stochastic intraseasonal production functions within an economic model of field-level irrigation decision making in order to predict optimal land and water use choices under groundwater supply constraints.

2.1. Crop Model

In this study the crop simulation model AquaCrop is used to simulate crop growth, crop yield and total seasonal irrigation in response to different intraseasonal irrigation strategies formulated in terms of soil moisture management. AquaCrop is a water-limited yield model developed by the Food and Agriculture Organization of the United Nations (FAO) [*Raes et al*., 2012]. The model was designed for use by a diverse range of practitioners and is therefore executable through a user interface system, reducing the ability to apply the model in integrated hydro-economic analyses. To aid integration, we chose to recode AquaCrop into the Matlab programming language [*Mathworks Inc*., 2013]. Test simulations were conducted for a range of crops and environmental conditions, verifying the accuracy of the recoding process.

AquaCrop simulates above and below-ground processes across the soil-vegetation-atmosphere continuum on a daily time step at the field-scale. Model inputs include soil and crop characteristics, daily weather data (maximum and minimum temperature, precipitation, and computed reference evapotranspiration), and irrigation management practices. The model uses a water-driven growth equation to translate simulated transpiration into accumulated above-ground biomass using a crop-specific water productivity parameter [*Steduto et al*., 2007]. Crop yield is then calculated as the product of simulated above-ground biomass and crop harvest index. Crop growth processes are affected by water stress, dependent on both the level of soil water depletion and the sensitivity of the specific biological process to water stress.

For the purposes of this study, AquaCrop offers a number of advantages over alternative crop simulation models. The grounding of AquaCrop in biophysical crop-water relations and its ability to consider a variety of irrigation management strategies make the model ideally suited for analyzing crop-water production relationships. Furthermore, the model is substantially less complex and requires fewer parameters than most crop simulation models. This is beneficial when seeking to apply the model within an integrated framework for the purposes of water resources management. AquaCrop has also been successfully applied to a wide variety of crops in a diverse range of geographic locations, including corn production in the United States [*Heng et al.*, 2009; *Hsiao et al.*, 2009; *Mebane et al.*, 2013] and elsewhere [*Stricevic et al.*, 2011; *Abedinpour et al.*, 2012; *García-Vila and Fereres*, 2012].

2.2. Production Function Development

The simplest formulation of the crop-water production relates the mean crop yield return, Y, to total seasonal irrigation, X, as in equation (1).

$$Y=f(X) \tag{1}$$

However, actual production returns to irrigation are not constant and will be affected by climatic conditions and management choices. Weather variability is a particularly significant driver of variability in irrigation water demand. Equation (1) can therefore be extended to account for the impact of interannual weather variability on crop yield return to seasonal irrigation. Crop simulation models are valuable tools for this purpose, and, as previously noted, can be used to derive stochastic crop-water production functions by iteratively generating multiple functions using weather time series given the functional relationship in equation (2).

$$Y_t=f(X,\theta_t) \tag{2}$$

Where Y_t is yield in year t, and θ_t are weather variables in year t. The weather variables considered commonly include temperature and precipitation, although the exact variables used and their temporal resolution will vary according to the requirements of the selected crop simulation model. Note that in equation (2), X still denotes the total seasonal irrigation.

In this study we build on the formulation of the crop-water production function given in equation (2) by developing stochastic intraseasonal crop-water production functions that are more consistent with observed irrigation behavior. The developed production functions introduce two key innovations over equation (2): (1) the irrigation decision is represented by the selection of an intraseasonal soil moisture target as opposed to the choice of a total seasonal irrigation depth; (2) the production function varies in response to both weather variability and differences in instantaneous application rates imposed by well yield. The mathematical formulation of the production function is detailed in equation (3), and the calculation framework and basis for each model innovation are described below.

$$\begin{aligned} &Y_t=f\left(x_t^{i\ldots n},\theta_t\right)\\ &X_t=\sum_{i=1}^{n}x_t^i=f(S,\theta_t)\\ &s.t.\\ &0\le x_t^i\le x_{\max}\,\forall x\\ &x_{\max}=f(W,A) \end{aligned} \tag{3}$$

Where x_t is a vector of daily irrigation applications in year t of length n where n is the number of days in the growing season, X_t is the total irrigation use in year t, S is the intraseasonal soil moisture target equal to a specified proportion of potential plant available water (defined as the water held between field capacity and permanent wilting point integrated across the crop root zone) at which irrigation is initiated during the growing season, x_{max} is the maximum daily irrigation rate, W is the well yield, and A is the irrigated area.

In the first step of the simulation framework AquaCrop is applied to predict crop yield and total seasonal irrigation demand in response to a range of intraseasonal soil moisture targets, given specific weather

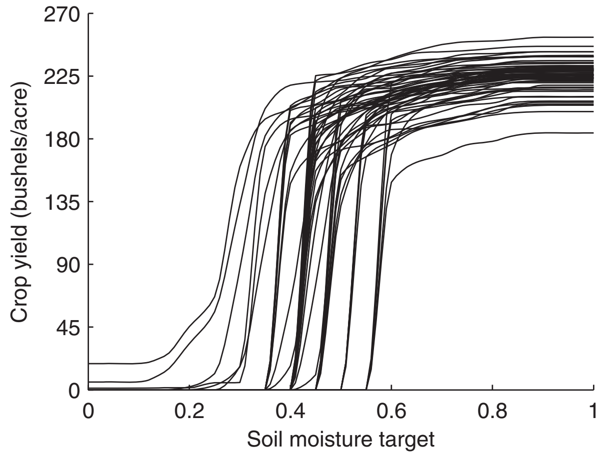

Figure 1. Stochastic relationship, due to interannual weather variability, between the soil moisture target and per-area corn yield (bu/ac). Each line represents the individual relationship for a simulation by AquaCrop using one of 55 years of daily weather data recorded at Amarillo, Texas, obtained from the National Oceanic and Atmospheric Association Global Summary of the Day data set. Note: 1 bu/ac is equal to 0.063 tonne/ha.

inputs, using the relationship as in equation (3). Nonparametric functions are fitted to the generated data points using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) function in MATLAB [*Mathworks Inc*., 2013]. Crop growth and crop yield production are both fundamentally dependent on the maintenance of adequate soil moisture during the growing season [*Steduto et al*., 2009]. Consequently, an extensive body of literature has examined the important role that management of soil moisture plays in the planning and optimization of irrigation decisions [*Shani et al*., 2004; *Wang and Cai*, 2007; *Vico and Porporato*, 2011; *Alizadeh and Mousavi*, 2013]. However as stated earlier, existing crop-water production functions employed in integrated hydro-economic models use total seasonal irrigation as the model decision variable and do not explicitly consider the role of soil moisture in irrigation decision making. A number of approaches have been used to address the temporal mismatch between the intraseasonal time step of irrigation decision making and crop/hydrological model simulation, and the seasonal resolution of the crop-water production function. *Nair et al*. [2013] suggest assuming a fixed number of days between individual irrigation events. Contrastingly, *Schütze and Schmitz* [2010] optimize the daily scheduling of irrigation within the growing season according to daily variation in crop water demands to obtain the highest potential crop yield for a given total seasonal depth of irrigation. Similarly, *Cai* [2008] introduce a penalty function to ensure that the distribution of total seasonal irrigation throughout the growing season is optimized according to the monthly variability in crop-water requirements and yield sensitivity to water stress. The latter two approaches, in particular, are advantageous as they capture the fact that farmers actual irrigation scheduling will be dependent on the variation in crop water requirements during the growing season. However, by optimizing intraseasonal irrigation scheduling these models are implicitly conditioned on the farmer having perfect foresight of crop water requirements throughout the growing season. As crop water requirements vary according to weather conditions, this therefore creates an unrealistic assumption that the farmer knows in advance weather conditions exactly for the entire growing season. Contrastingly, by describing the production decision in terms of the intraseasonal management of soil moisture, equation (3) is able to provide a more realistic and flexible representation of the farmer's actual irrigation decision-making process. Specifically, equation (3) reflects that the decision on when to irrigate and how much water to apply are made solely on the basis of the current state of soil moisture without any assumptions about conditions in the future growing period.

The calculations of crop yield and irrigation requirements described in step one are conditioned on weather inputs for a single growing season and assume a biophysically unrestricted maximum daily irrigation rate, defined by the specified upper bounds of well yield and irrigated area, that allows the farmer to always meet full crop water requirements on the maximum available irrigated area. To account for production differences introduced by interannual weather variability, in step two the procedure described above is repeated for multiple growing seasons of weather data for the site or region of interest. Weather time series

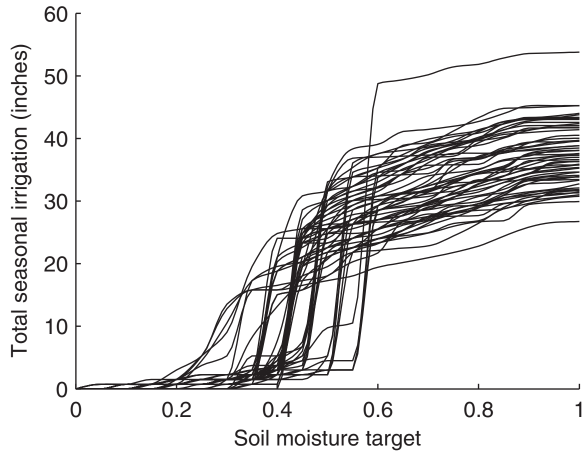

Figure 2. Stochastic relationship, due to interannual weather variability, between the soil moisture target and per-area total seasonal irrigation use (in). Each line represents the individual relationship for a simulation by AquaCrop using one of 55 years of daily weather data recorded at Amarillo, Texas, obtained from the National Oceanic and Atmospheric Association Global Summary of the Day data set. Note: 1 in is equal to 25.4 mm.

may be obtained from historic weather records or, alternatively, may be synthetically generated using a numerical weather generator. The resulting output captures the potential distribution of crop yields (Figure 1) and total irrigation requirements (Figure 2) for each soil moisture target. Significantly, Figures 1 and 2 illustrate that soil moisture management decisions will be based upon expectations not only about final crop yield (as is the case in equations (1) and (2)), but also about the total amount of irrigation water that will be required over the season to maintain soil moisture above a target threshold. Accounting for this uncertainty in expected irrigation requirements will be important in situations of limited water availability, where the inability to maintain adequate soil moisture levels in dry years may lead to changes in irrigation behavior to mitigate potential production losses and risks.

The intraseasonal structure of the production function in equation (3) also provides a valuable means of considering the impact of groundwater supply constraints on the crop-water production function. Variations in well yield place an upper bound on the instantaneous rate at which irrigated can be applied to a specific area in a given time period. This in turn will affect the ability to maintain sufficient soil moisture in the root zone with resultant negative impacts on crop yield, net returns, and production risk [*O'Brien et al.*, 2001; *Peterson and Ding*, 2005; *Lamm et al.*, 2007; *Colaizzi et al.*, 2009; *Wines*, 2013]. However as previously noted, instantaneous application constraints have been neglected in existing simulation modeling approaches to generate crop-water production functions. In the third step of our calculation framework we repeat the simulations in steps one and two to generate stochastic intraseasonal production functions for each unique possible combination of irrigated area size and well yield, which together define the maximum depth of water that can be applied to the field in a given time period (equation (3) and Figure 3). In this study the time period is defined as a calendar day, consistent with the temporal resolution of both AquaCrop and real-world irrigation planning. Consequently, the complete stochastic intraseasonal crop-water production function describes the relationship between soil moisture target and crop yield, and between soil moisture target and total irrigation demand, accounting for the variability in these functions induced by both weather and instantaneous application rate constraints.

2.3. Economic Producer Decision-Making Model

The farmer's decision-making process with regard to irrigation has two components, namely the intensive and extensive margin decisions. The intensive margin refers to the per-area irrigation intensity, and is represented by the choice of an intraseasonal soil moisture target which determines expectations of per-area crop yields (Figure 1) and irrigation requirements (Figure 2). The extensive margin refers to the size of irrigated area, and reflects the preseason planting decision made by the farmer. As irrigation is used by farmers to mitigate production variability, attitude to production risk may have an impact on optimal irrigation behavior. In order to consider a range of risk preferences in our analyses, the optimal choice of irrigated

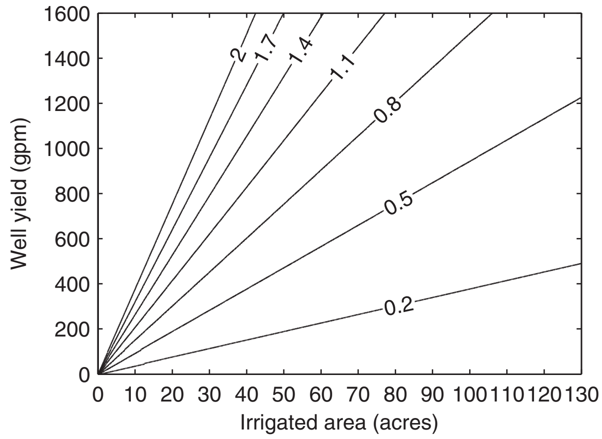

Figure 3. Contours of maximum daily irrigation application rates (in) for different combinations of well yield (gpm) and irrigated area size (ac). The calculations assume a single well operating a center-pivot irrigation system that can effectively irrigate up to 130 ac of a typical 160 ac quarter-section plot (52.6 ha of a 64.7 ha plot). Note: 1 ac is equal to 0.4 ha, 1 gpm to 0.06 l/s, and 1 in to 25.4 mm.

area and per-area irrigation intensity are therefore formulated as a certainty equivalent (CE) maximization procedure. The CE represents the certain level of payoff which the farmer considers equally desirable in terms of utility to some uncertain payoff [*Chavas*, 2004], and is calculated as the difference between the expected profit, $E(\pi)$, and the risk premium, RP, as in equation (4).

$$CE=E(\pi)-RP \tag{4}$$

Commonly, CE maximization requires the moments of the crop-water production to be statistically defined in order to predict the moments of yield or profits [*Antle*, 1983; *Just and Pope*, 1978]. To do this, assumptions must be made about the specific functional form of the moments of the production relationship. Given the complex variation in the relationships between the soil moisture target and crop yield (Figure 1), and between the soil moisture target and total irrigation demand (Figure 2), specification of a fixed functional form has the potential to induce errors in subsequent analyses [*Finger*, 2012]. In this study, we therefore choose not to specify a particular functional form for the moments of the production relationship. Instead, we maximize the CE using a procedure designed to represent realistically the temporal structure of actual optimal decision making.

The CE maximization procedure begins by calculating the profit-maximizing soil moisture target and associated profit for each possible size of irrigated area, given a specific well yield, as in equation (5). Profit for a given irrigation strategy is calculated as the difference between the income generated from crop yield and the fixed and variable costs of production. Fixed costs are incurred for seeds, fertilizers, herbicides, insecticides, crop insurance, farm equipment and machinery, labor, and repairs and maintenance. Variable costs include the costs of applying each unit of water in terms of fuel and labor, along with the costs incurred for harvesting each unit of yield.

$$\begin{aligned}
&\left[\pi^*_{j,t}, S^*_{j,t}\right]=\max_S \begin{bmatrix} Y_{j,t}\left(x_t^{i\ldots n}(S,\theta_t)|A_j,W\right)\cdot A_j\cdot(p_c-p_h) \\ -A_j\cdot c_f-X_{j,t}\left(S,\theta_t|A_j,W\right)\cdot c_v \end{bmatrix} \\
&s.t. \\
&X_{j,t}\cdot A_j\leq Q
\end{aligned} \tag{5}$$

Where $\pi^*_{j,t}$ and $S^*_{j,t}$ are the maximized profit and profit-maximizing soil moisture target, respectively, in year t on irrigated area j, A_j is the irrigated area, p_c is the crop price, p_h is the price of harvesting the crop, c_f are the fixed costs of production, c_v are the variable costs of irrigation, and Q is the total seasonal water supply.

Equation (5) uses a single intraseasonal crop-water production function, generated for a specific growing season. The feasible set of irrigation strategies is restricted by a constraint on total seasonal water supply, Q, which may limit the range of soil moisture targets that are attainable on a given size of irrigated area.

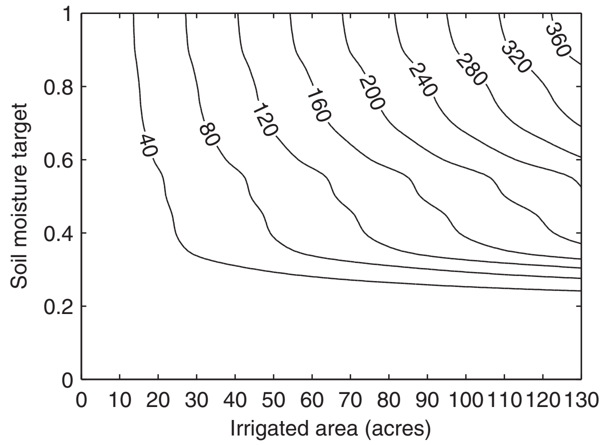

Figure 4. Contours of total irrigation use (ac ft) for corn production given different combinations of per-area irrigation intensity (soil moisture target) and irrigated area (ac). Data were generated by AquaCrop using daily weather data recorded at Amarillo, Texas, for a year with average growing season rainfall (2007) obtained from the National Oceanic and Atmospheric Association Global Summary of the Day data set. Note: 1 ac ft is equal to 1.2 Ml, and 1 ac is equal to 0.4 ha.

Figure 4 illustrates this concept showing how, in a particular year, total volumetric water requirements vary for different possible combinations of extensive and intensive margin decisions. Importantly, this constraint ensures that predictions of expected profitability explicitly account for potentially reduced production due to regulatory restrictions on total annual abstraction. Indeed, regulatory restrictions are likely to be a key factor influencing optimal irrigator behavior in areas where they are used to tackle problems of groundwater depletion.

The calculations in equation (5) are repeated using the intraseasonal crop-water production functions for all individual growing seasons in turn to produce profit distributions for each possible size of irrigated area. Using these distributions expected maximized profit, $E(\pi^*)$, and maximized profit variance, $\sigma^2_{\pi^*}$, are then calculated for each possible discrete choice of irrigated area. Following *Antle* [1987], these values are used to calculate the risk premium for each potential irrigated area (equation (6)), assuming constant relative risk aversion, where r is the Arrow-Pratt coefficient of relative risk aversion. Note that when $r=0$ then the producer is assumed to be risk neutral and the CE is simply equal to expected profits. Contrastingly, values of $r > 0$ reflect increasingly risk-averse behavior.

$$RP(A|W,S^*)=0.5\cdot\frac{\sigma^2_{\pi^*}(A|W,S^*)\cdot r}{E(\pi^*(A|W,S^*))} \tag{6}$$

Finally, given values of expected maximized profit and risk premium for all possible choices of irrigated area, it is then straightforward to compute the optimal irrigation strategy by maximizing the CE with respect to the choice of irrigated area (equation (7)), given the previously specified well yield. It is important to note that for computational simplicity, the model setup assumes that the nonirrigated portion of the field has no economic value. In reality, the farmer may be able to extract value through rainfed production or other strategies, such as environmental stewardship. Predictions of optimal irrigated area should therefore be seen as upper bounds, as if nonirrigated production has a positive marginal value then this will increase the potential optimality of extensive margin adjustments.

$$\max_A\ CE=E(\pi^*(A|W,S^*))-0.5\cdot r\cdot\frac{\sigma^2_{\pi^*}(A|W,S^*)}{E(\pi^*(A|W,S^*))} \tag{7}$$

Maximizing CE in terms of the choice of irrigated area instead of per-area irrigation intensity provides a behaviorally realistic representation of the temporal structure of optimal irrigation decision making. Specifically, it captures the fact that farmers make planting decisions preseason based upon uncertain expectations of growing season weather and guidance about required well pumping capacities to ensure sufficient irrigation supply [e.g., *New and Fipps*, 2002; *Kranz et al.*, 2008]. Farmers subsequently are unlikely to abandon irrigation on the planted area due to the losses this would incur as a result of the significant fixed costs that must be invested early in the growing season. Contrastingly, intensive margin decisions are made intraseasonally on the basis of soil moisture changes and may be adjusted as the growing season evolves and additional knowledge is gained about weather conditions and other variables. In this regard the CE calculation implicitly assumes that the farmer will manage to the derived profit-maximizing soil moisture target in each growing season, and we do not model the impacts of deviations from this optimal strategy which may reduce actual profits.

3. Case Study Application

We apply the developed methodology to a case study of irrigated corn production in the Texas High Plains region of the United States in order to understand the impact of limited groundwater supply on irrigation behavior and to assess the ability of existing crop-water production functions to provide robust predictions of irrigation decision making and agricultural groundwater demand. Corn is a major irrigated crop in the Texas High Plains region (data obtained from: http://www.nass.usda.gov/Quick_Stats), with irrigation providing a crucial buffer against variable precipitation patterns and high levels of evaporative demand. Typically irrigation is managed using a center-pivot sprinkler system which can effectively irrigate 130 acres of a 160 acre quarter section plot (52.6 ha of a 64.7 ha plot). Irrigation water is sourced almost entirely from groundwater stored in the underlying Ogallala Aquifer. However, abstraction for irrigation over past decades has far exceeded rates of natural recharge, resulting in substantial water table declines [*McGuire et al*., 2012; *Scanlon et al*., 2012] and reductions in well yield [*Colaizzi et al*., 2009]. Declines in well yield have had large impacts on farmer behavior in the Texas High Plains region, leading to significant reductions in irrigated area and production per well over recent decades [*Texas Water Development Board*, 2001; *Klocke et al*., 2004; *Colaizzi et al*., 2009]. These declines are predicted to be exacerbated in the years to come given rates of depletion that are expected to further lower water levels and reduce well yields [*Scanlon et al*., 2012; *Texas Water Development Board*, 2012]. The long-term sustainability of irrigated agriculture in the Texas High Plains therefore is a key concern for farmers and water managers [*Marek et al*., 2013]. Hence, tools are needed to predict how agricultural producers may respond to increasingly constrained levels of groundwater supply. In turn, these local-level predictions will provide valuable information to help guide the development of aquifer-scale policies to balance competing demands for increased agricultural production and sustainable groundwater management.

3.1. Production Function Generation

We focus our numerical analysis on a specific location in the Texas High Plains, Moore County, which accounts for a substantial proportion of the total irrigated corn area in the region (data obtained from: http://www.nass.usda.gov/Quick_Stats). No weather station with a sufficient record length exists in Moore County. Weather data recorded at Amarillo in neighboring Potter County, obtained from the National Oceanic and Atmospheric Association Global Summary of the Day data set (available at: ftp://ftp.ncdc.noaa.gov/pub/data/gsod), are therefore used as the basis for generating the stochastic intraseasonal crop-water production functions. The weather station at Amarillo provides daily values of maximum and minimum temperature, dew point temperature, total precipitation, and average wind speed over the period 1943–2013. Global Summary of the Day data undergoes a range of quality control measures [*Durre et al*., 2010]. However despite these, 16 of the 71 record years (1943–1946, 1965–1973, 1981, and 1992–1993) are not used in the generation of production functions as in these years greater than 10% of days contain missing data in one or more variable. For the 55 years that are retained, the final weather input variable required by AquaCrop, reference evapotranspiration, is computed using the standardized ASCE Penman-Monteith equation [*Allen et al*., 2005]. At a daily time step the ASCE Penman-Monteith formula is identical to the FAO-56 Penman-Monteith equation, and as such is the recommended method for estimating reference evapotranspiration [*Allen et al*., 1998; *Allen et al*., 2005]. The ASCE Penman-Monteith equation has also been shown to perform better than alternative equations (e.g., Hargreaves, Penman, and Kimberley-Penman) in the High Plains region of the United States where high winds and vapor pressure deficits have large impacts on reference evapotranspiration [*Itenfisu et al*., 2003]. Furthermore, the ASCE Penman-Monteith equation was used as the basis for estimating reference evapotranspiration in the calibration of AquaCrop for corn at Bushland in Texas [*Heng et al*., 2009] thus providing consistency with the methods used to develop the crop parameters applied in this paper.

10.1002/2014WR015620

Table 1. Parameter Values for Economic Producer Decision-Making Model

Parameter	Value
Corn price ($/bu)	5.5
Coefficient of risk aversion	0–4
Fixed Costs ($/ac)	
Seeds	119
Insecticide	25
Herbicide	36
Fertilizer	161.25
Crop insurance	20
Labor	12.02
Fuel	16.41
Repair and maintenance	41.25
Nonirrigation machinery and equipment	23.5
Center-pivot	50
Interest on operating capital	15.62
Variable Costs	
Irrigation fuel ($/ac-in)	1.80
Irrigation labor ($/ac-in)	0.67
Crop drying and harvesting ($/bu)	0.40

It is assumed in the calculation of the production functions that the corn crop was planted on May 1 each year with a planting density of 30,000 plants/ac (74,132 plants/ha) characteristic of typical agronomic practices in the region [*National Agricultural Statistics Service*, 2010]. Following *Lamm et al*. [2007], soil moisture levels at the start of the growing season are set at 85% of field capacity throughout the soil profile indicative of some degree of rainfall or preseason irrigation before planting. Soil type in AquaCrop is defined to represent a Sherm silty clay loam soil. This soil is the most commonly cropped soil type for corn production in Moore County, as identified by a comparison of the spatial distribution of soils in the county given in the SSURGO data set (available at: http://websoilsurvey.nrcs.usda.gov) with the historic (2009–2013) distribution of corn production areas (data obtained from: http://nassgeodata.gmu.edu/CropScape). Based on these soil data, we assume textural properties of 23% sand, 46% clay, 31% silt, and an organic matter content of 0.66%. Soil textural properties are subsequently used to calculate soil hydraulic properties for AquaCrop using a pedotransfer function approach [*Saxton et al*., 1986]. Crop growth parameters in AquaCrop are defined according to a previous calibration of AquaCrop in the Texas High Plains at Bushland, Potter County [*Heng et al*., 2009], which demonstrated that AquaCrop was able to reproduce corn growth and yield under a range of irrigation conditions.

Using the parameters and weather inputs described above, AquaCrop is applied to simulate crop yield and total irrigation requirements for a range of soil moisture targets using the procedure described in section 2.2. The soil moisture target is varied from 0, representing permanent wilting point, to 1, indicative of field capacity, in increments of 0.05 to capture the complete range of potential soil moisture management strategies that are available to the farmer. When irrigation is triggered water is considered to be applied uniformly over the full irrigated area during a single day in order to bring the soil water content back to field capacity. The maximum daily irrigation rate is, however, limited by the instantaneous application constraint imposed by well yield and irrigated area. It is also assumed that 10% of the irrigation water applied does not reach the root zone, which is typical of application losses from a center-pivot system in the region [*Wagner*, 2012]. Well yield is discretized from 0 to 1600 gallons per minute (gpm) (0–101 l/s) in increments of 20 gpm (1.3 l/s) to represent a broad range of possible well yields. Irrigated area size is varied from 0 to 130 ac (0–52.6 ha) in increments of 1 ac (0.4 ha). This range in potential irrigated area is characteristic of the size of a typical center-pivot irrigation system operating on a quarter section field. Additionally, the fine level of discretization reflects the fact that the size of irrigated area can be relatively easily adjusted by altering the extent of pivot rotation or length of the sprinkler arm.

3.2. Model Simulations

Using the generated stochastic intraseasonal crop-water production function we evaluate the impact of seasonal and intraseasonal groundwater supply constraints on optimal irrigator behavior. Different intraseasonal groundwater supply restrictions, which limit the instantaneous rate at which groundwater can be

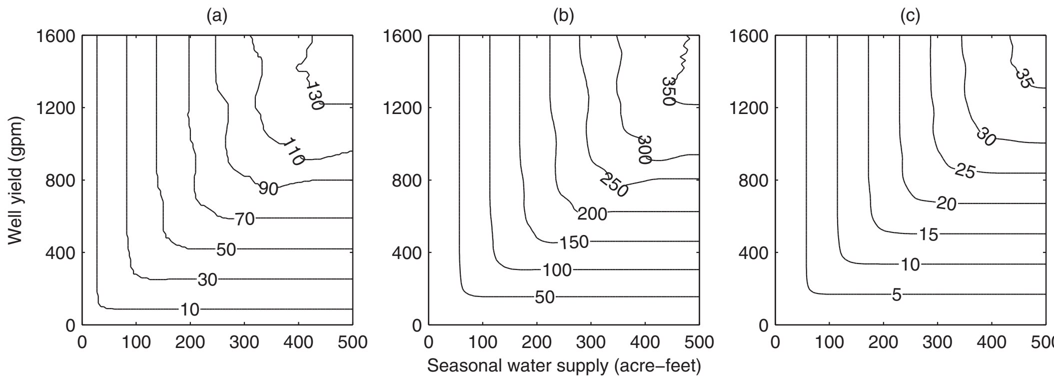

Figure 5. Predicted contours of optimal: (a) Irrigated area (ac); (b) Total irrigation use (ac ft); and (c) Profits (US$1000) for different seasonal (ac ft) and intraseasonal (gpm) groundwater supply restrictions. Note: 1 ac ft is equal to 1.2 Ml, 1 ac to 0.4 ha, and 1 gpm to 0.06 l/s.

abstracted, are represented by the discretized values of well yield, ranging from 0 to 1600 gpm (0–101 l/s). The seasonal groundwater supply constraint reflects regulatory restrictions that are increasingly being applied in the High Plains region of the USA to limit the volume of groundwater that farmers can abstract per growing season [*Kuwayama and Brozović*, 2013; *Brozović and Young*, 2014], and is varied from 0 to 500 ac ft (0–617 Ml) in 10 ac ft (12.3 Ml) increments. The range of both seasonal and intraseasonal supply constraints is designed to cover a spectrum of conditions from no supply to effectively unrestricted pumping. We apply each possible combination of seasonal and intraseasonal groundwater supply restrictions in turn within the CE maximization procedure detailed in section 2.3 to determine optimal irrigation strategies and expected farm-level profitability. Economic values needed to parameterize equation (5) are taken from *Texas AgriLife Extension Service* [2013] and are summarized in Table 1. To account for the relative role of risk preferences in irrigation decision making we repeat the analyses detailed for different levels of risk aversion. The coefficient of relative risk aversion, r, is varied from 0 (risk neutral) to 4 (highly risk averse) in increments of 0.5.

3.3. Model Comparison

We seek to compare the results given by the analysis in section 3.2 with those that would be obtained when using a stochastic seasonal formulation of the crop-water production function (equation (2)) that commonly has been applied to model irrigation decision making. As noted previously, existing crop-water production functions differ from our stochastic intraseasonal production function in two ways. Specifically, they do not consider the impact of instantaneous application constraints imposed by well yield or the role of soil moisture as a key decision variable. Therefore, we generate stochastic seasonal production functions by repeating the simulations described in section 2.2 but with no constraint on instantaneous application rates applied. The simulated relationships between the soil moisture target and crop yield, and between the soil moisture target and total irrigation demand, are then aggregated to produce data points of crop yield return to total seasonal irrigation to reflect that existing production functions do not consider soil moisture as a decision variable. Using these data points we fit a nonparametric relationship for each growing season using the PCHIP function in MATLAB [*Mathworks Inc*., 2013] to generate a stochastic seasonal crop-water production function as per equation (2). We apply the stochastic seasonal crop-water production function to predict optimal irrigation decision making in terms of the preseason choice of irrigated area using the same CE maximization procedure as described in section 2.3. Optimal decisions are, however, only calculated for constraints on seasonal water supply due to the inability of seasonal crop-water production functions to capture intraseasonal groundwater supply constraints induced by well yield. Importantly, by applying the same optimization methodology as when using our developed stochastic intraseasonal crop-water production functions we are able to isolate the impact of the choice of production function on simulated irrigation decision making. This provides useful information about the value obtained from our stochastic intraseasonal crop-water production function and highlights the situations where use of existing production functions may lead to unreliable predictions of irrigation decision making.

4. Model Results and Discussion

4.1. Irrigation Behavior

Our results demonstrate that farmers' irrigation behavior exhibits complex nonlinear responses to changes in groundwater availability. In particular, by allowing the crop-water production function to vary as a function of the constraint on maximum daily application rates, we find that the optimal size of irrigated area (Figure 5a) and total irrigation demand (Figure 5b) for a risk neutral farmer are variable in response to both seasonal and intraseasonal groundwater supply constraints. Significantly, we observe three different kinds of behavior where the optimal size of irrigated area is primarily: (1) unconstrained; (2) seasonally constrained; (3) intraseasonally constrained.

Under conditions of extensive seasonal ($>$400 ac ft /493 Ml) and intraseasonal ($>$1200 gpm/76 l/s) groundwater supply it is shown that the optimal decision is to irrigate the full, or close to the full, 130 ac (52.6 ha) production area (Figure 5a). When irrigated area is at or close to its maximum limit, Figure 5b demonstrates that total irrigation use may decline slightly as a result of intensive margin adjustments. Such water savings are primarily motivated by reductions in seasonal groundwater allocation that necessarily limit the attainable soil moisture target and irrigation intensity on the full production area particularly in the driest years.

As seasonal groundwater supply is reduced below 350–400 ac ft (430–490 Ml) irrigation decision making becomes more limited by seasonal groundwater supply constraints. Irrigated area size (Figure 5a) and total irrigation demand (Figure 5b) both decline at approximately linear rates. These changes reflect the increasing use of extensive margin adjustments to provide the water savings necessary to meet restrictive regulatory constraints, which limit the ability to manage soil moisture levels effectively to avoid significant crop yield losses. Importantly, intraseasonal supply constraints become progressively less influential as shown by the increasingly vertical slope of the contours with respect to seasonal water supply for seasonal groundwater allocations below 350–400 ac ft (432–493 Ml) (Figures 5a and 5b). Intuitively, this reveals that, for low seasonal groundwater allocations, potential changes in instantaneous application rates have less impact on optimal irrigation decisions as any additional intraseasonal water supply capacity obtained from a higher well yield will be unusable due to the binding seasonal water supply constraint.

Contrastingly, we observe that constraints on instantaneous application rates imposed by well yield have a significant effect on irrigation behavior for moderate to large seasonal groundwater allocations. As seasonal supply restrictions are relaxed, irrigation behavior becomes increasingly sensitive to reductions in well yield below approximately 1000–1200 gpm (63–76 l/s). Intraseasonal impacts are particularly evident for seasonal water supplies above around 150–200 ac ft (185–247 Ml), where rapid declines occur in the optimal size of irrigated area (Figure 5a) and total irrigation use (Figure 5b) even as seasonal groundwater allocation is held constant. Biophysically, these extensive margin adjustments can be explained by the need to maintain daily application rates at a level that avoids severe perpetual soil moisture deficits and resultant crop water stress (see Figure 3). By reducing irrigated area and relaxing the constraint on daily irrigation rates, the farmer is able to maintain higher soil moisture levels and obtain a larger average per-area crop yield. At the same time reductions in irrigated area also lower the total fixed costs of production, and it is the combination of these two factors that leads to increased optimality of partial-area irrigation when well yield is limiting.

4.2. Profits

Our model analyses also provide estimates of the impact of groundwater supply constraints on field-level profitability. Figure 5c illustrates that expected profits are highly correlated with the patterns of irrigation behavior observed in Figures 5a and 5b. Expected profits therefore exhibit marked sensitivity to both seasonal and intraseasonal groundwater supply constraints.

Expected profits for the 130 ac (52.6 ha) field are highest, greater than $US 35,000 per cropping season, where both seasonal and intraseasonal groundwater supply are at a maximum. As seasonal groundwater supply is reduced, expected profits decline at a slower initial rate due to the initial implementation of intensive margin adjustments and resultant small to moderate reductions in per-area crop yield for seasonal supplies greater than 350–400 ac ft (432–493 Ml). This is followed by a larger, approximately linear decline in

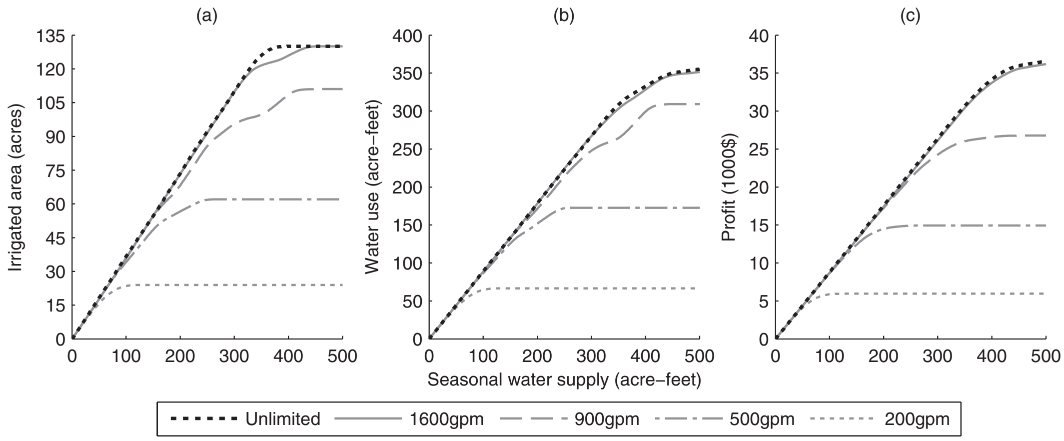

Figure 6. Predictions of optimal: (a) Irrigated area (ac); (b) Total irrigation use (ac ft); and (c) Expected profits (US$1000) for different seasonal groundwater supply (ac ft) restrictions. The black dashed line denoted "unlimited" refers to predictions from a stochastic seasonal crop-water production function with unrestricted well yield. Contrastingly, the grey lines denoted "1600 gpm," "900 gpm," "500 gpm," and "200 gpm" refer to predictions obtained when using our stochastic intraseasonal crop-water production function assuming well yields of 1600, 900, 500, and 200 gpm (101, 57, 32, and 13 l/s) respectively. Note: 1 ac ft is equal to 1.2 Ml, 1 ac to 0.4 ha, and 1 gpm to 0.06 l/s.

profits as the farmer switches permanently to extensive margin adjustments for seasonal groundwater allocations below around 350 ac ft (432 Ml) to stabilize crop yields and reduce fixed costs.

Profit reductions due to intraseasonal supply constraints are most noticeable for moderate to high levels of seasonal groundwater supply (>150–200 ac ft/185–247 Ml). In this region, well yield may become a limiting factor for profit generation at levels as high as around 1000–1200 gpm (63–76 l/s) depending on the level of the seasonal groundwater supply. The reduction in expected profitability reflects the fact that binding intraseasonal supply constraints imposed by well yield limit the range of soil moisture targets that farmers can effectively manage for a given seasonal groundwater allocation. In order to achieve optimal expected crop yields and profits farmers must reduce the size of their irrigated operation, both in terms of the size of irrigated area and total water use, below the level that would be attainable with a higher well yield and the same seasonal groundwater allocation. Consequently, the farmer forgoes a large proportion of potential profits for a given seasonal groundwater allocation due to the physical intraseasonal constraints imposed by the hydrogeological system.

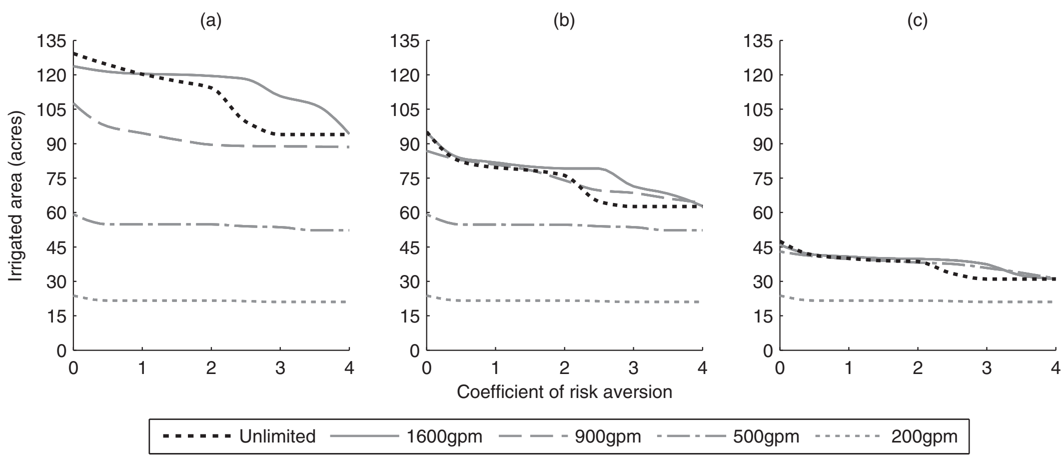

Figure 7. Predictions of optimal irrigated area (ac) for different levels of risk aversion given seasonal groundwater allocations of: (a) 390 ac ft (481 Ml); (b) 260 ac ft (321 Ml); and (c) 130 ac ft (160 Ml). The black dashed line denoted "unlimited" refers to predictions from a stochastic seasonal crop-water production function with unrestricted well yield. Contrastingly, the grey lines denoted "1600 gpm," "900 gpm," "500 gpm," and "200 gpm" refer to predictions obtained when using our stochastic intraseasonal crop-water production function assuming well yields of 1600, 900, 500, and 200 gpm respectively (101, 57, 32, and 13 l/s).

4.3. Model Comparison

The results shown in section 4.2 can be compared to predictions of optimal irrigation behavior obtained when using existing models of irrigation decision making. In doing so we are able to examine the ability of current crop-water production functions to provide reliable predictions of field-level irrigation decisions, which often are used to inform larger scale groundwater management and policy development.

Given a stochastic seasonal crop-water production function as a benchmark for existing models, Figures 6a and 6b illustrate how the optimal size of irrigated area and total irrigation use, respectively, vary as a function of seasonal groundwater supply. For ease of comparison, predictions obtained when using our stochastic intraseasonal crop-water production function are only shown for a selection of well yields. When using an existing crop-water production function, we predict that water savings are initially achieved through intensive margin adjustments, followed by a permanent switch to extensive margin adjustments for seasonal groundwater allocations of 350 ac ft (432 Ml) or less. This pattern of deficit irrigation behavior is almost identical to that predicted when using our stochastic intraseasonal crop-water production function given a very high well yield (e.g., 1600 gpm/101 l/s). However, as well yield is reduced there is an increasing divergence in model predictions. Specifically, use of existing crop-water production functions leads to increasing overprediction of the optimal irrigated area for seasonal water allocations of around 100 ac ft (123 Ml) or more. This result can be explained by the failure of existing crop-water production functions to account for constraints on instantaneous application rates due to well yield, which have been shown in section 4.1 to be a key driver of changes in the optimal size of irrigated area. In turn, overprediction of the optimal size of irrigated area has a significant effect on predictions of expected field-level profitability. Figure 6c shows that the inability to capture the large extensive margin adjustments in response to limited well capacity leads to overprediction of expected profits for moderate to high seasonal water supplies. Indeed, maximum expected profits derived from a stochastic seasonal crop-water production function are approximately 36% higher than those given by our stochastic intraseasonal crop-water production function for a well yield of 900 gpm (57 l/s). This difference expands further to 144% given a well yield of 500 gpm (32 l/s), and 513% for a well yield of 200 gpm (13 l/s).

4.4. Sensitivity to Risk Aversion

Figure 7 summarizes how optimal irrigated area size varies as a function of the specified degree of risk aversion for seasonal groundwater allocations of: (a) 390 ac ft (481 Ml); (b) 260 ac ft (321 Ml); and (c) 130 ac ft (160 Ml). The results are reported for the same set of model formulations used in section 4.3.

In general, increasing risk aversion leads to further reductions in the optimal size of irrigated area. This trend indicates the farmer's willingness to choose a smaller irrigated production area in order to increase per-area water supply and reduce variance in profits caused by interannual weather variability and limited water availability. Declines in irrigated area size are most prominent for larger (260 or 390 ac ft/321 or 480 Ml) seasonal groundwater allocations. Changes for lower (130 ac ft/160 Ml) water supplies are limited as the binding seasonal water supply constraint dominates any changes in behavior due to risk aversion. Similarly, responsiveness to risk aversion is also affected by intraseasonal groundwater supply and, therefore, the choice of model formulation. The greatest reductions in irrigated area are found when using a stochastic seasonal model or our stochastic intraseasonal model given a high well yield (900 or 1600 gpm/57 or 101 l/s). As well yield, and thus instantaneous application rates are reduced, the impact of risk aversion on irrigator behavior diminishes.

It should also be noted that in some cases irrigated area is shown to decline more rapidly with increasing risk aversion when using a stochastic seasonal crop-water production than when applying our stochastic intraseasonal crop-water production function given a high well yield (e.g., Figure 7a). This result reflects that simply by imposing a physical limit on daily irrigation rates, irrigation schedules and feedbacks on other simulated hydrological processes such as deep percolation and surface runoff will be altered. The predicted certainty equivalents for each irrigated area size obtained when using our stochastic intraseasonal crop-water production function for a high well yield therefore are not necessarily identical to those obtained when using an existing production function that ignores well yield entirely. This may lead to slight divergence in predicted irrigated area with increasing risk aversion, such as that observed in Figure 7. Nevertheless, it is clear from a comparison of Figure 7 with Figures 5a and 6a that the extensive margin adjustments motivated by increasing risk aversion are substantially smaller than those predicted due to decreasing well yield under the assumption of risk neutrality.

4.5. Implications

This study highlights the importance of accounting for the structure and variables that influence farmers' real-world irrigation choices when attempting to model irrigation behavior and profitability. Previous studies have concluded that deficit irrigation will be an optimal adaptation to water supply restrictions in agriculture *[English*, 1990*; English et al*., 2002*; Fereres and Soriano*, 2007*; Evans and Sadler*, 2008*; Geerts and Raes*, 2009*; Wang and Nair*, 2013]. However, our analyses show that, in areas where groundwater is the main water supply source, the optimality of deficit irrigation is only valid for farms with access to high yielding abstraction wells. We demonstrate that when well yield is incorporated into predictions of field-level decision making the value of deficit irrigation as an adaptation to limited groundwater availability and extreme climate is greatly reduced. Specifically, we show that as well yield declines partial-area irrigation becomes increasingly optimal due to the impacts of constraints on instantaneous application rates on per-area crop yields and profits. This finding is comparable to the results obtained by *Baumhardt et al*. [2009] for cotton production in Texas, who show that low instantaneous application rates increase the optimality of partial-area irrigation. However, their analyses only consider three field partitioning scenarios, limiting the conclusions that can be drawn from the study. In addition, *Baumhardt et al*. [2009] also neglect to analyze the impacts of interactions between constraints on instantaneous application rates, seasonal groundwater supply restrictions and risk aversion, which our results demonstrate can have significant effects on the magnitude of well yield impacts on optimal decision making. Similarly, in another recent study of cotton in Texas, *Nair et al*. [2013] also show that field partitioning into irrigated and dryland portions can be optimal under conditions of limited water availability. However, their results do not fully account for the impact of well yield on optimal irrigation behavior as they focus on restrictions to seasonal water supply and do not explicitly impose limits on instantaneous application rates. The analyses reported here therefore provide the first thorough and robust study of the impacts of groundwater availability on irrigation decision making.

The results of this study also have implications for the use of integrated modeling for groundwater management and policy development. Integrated modeling frameworks currently used to study problems of irrigation-induced aquifer depletion [*Schoups et al*., 2006; *Harou and Lund*, 2008; *Maneta et al*., 2009; *Brozović et al*., 2010; *Bulatewicz et al*., 2010; *Varela-Ortega et al*., 2011; *Steward et al*., 2013] do not adequately account for the impact of well yield on agricultural production decisions or the dynamic trajectory of well yield with changes in aquifer saturated thickness. Whilst we do not model the dynamic evolution of the coupled human-water system in this study, our explicit analyses indicate that the failure of existing crop-water production functions, which are used to predict agricultural water demand in hydro-economic models, to account for the impacts of declining well yields may limit the applicability of existing models to predict future groundwater system trajectories and the effectiveness of policy options. Specifically, our results suggest that existing model projections will underestimate the negative impacts of reductions in groundwater availability on both rural economies and food security. Given the complex nonlinear relationships between groundwater levels, well yield, and irrigation decision making, we also hypothesize that a number of system thresholds affecting the ability to sustain irrigated agriculture may exist. Our findings suggest that sustaining saturated thicknesses at levels that do not significantly impact well yield and hence instantaneous irrigation application rates may have previously unrecognized economic value. An avenue for future work is thus to explore the extent to which policies that explicitly target the preservation of saturated thickness are feasible in regions of intensive groundwater-fed irrigation. In the context of the extensive Ogallala Aquifer system, we hypothesize that such policies may be most achievable in the Northern High Plains where, given that recharge rates are greatest [*Scanlon et al*., 2012] and substantial saturated thickness remains [*McGuire et al*., 2012], caps on groundwater abstraction may be able to stabilize water levels and well yields without unacceptable economic costs. Contrastingly, in the Southern High Plains recharge is minimal [*Scanlon et al*., 2012] and therefore it would most likely be cost prohibitive to reduce abstraction to levels necessary to avoid continuing well yield declines. In these areas future research should instead explore the economic value that may be gained by modifying the rate of well yield decline, for example through water restrictions or changing cropping practices, to sustain irrigated agriculture for longer periods into the future. Furthermore, in all cases analyses of optimal groundwater management must be set in the context of climate change and its potential impacts on recharge and crop water requirements [*Crosbie et al*., 2013] that undoubtedly will influence the success of policies aimed at managing saturated thickness and well yields.

4.6. Model Limitations

It is important to discuss some limitations of the developed model and the potential implications of these simplifications. First, we assume that the portion of the field that is not irrigated has no economic value. Whilst this choice reduces the computational demands of the final model, it is clearly an unrealistic representation of true practices. In reality, the farmer may be able to extract value from this additional area through either rainfed production or through other payments (e.g., for environmental services). Future modeling work should seek to model separately production decisions and expected outputs from both irrigated and nonirrigated portions of the field. However, it is not expected that adding nonirrigated production choices in conjunction with irrigated production would qualitatively alter the findings of this study. Indeed, *Nair et al*. [2013] show that the positive marginal value of the nonirrigated production area plays a role in increasing the optimality of partial-area irrigation under conditions of reduced seasonal water supply. As a result we expect that predicted extensive margin adjustments in response to declining well yields may be even larger than currently anticipated when the value of the nonirrigated area is considered.

A further simplification of our current modeling framework is the assumption that the intensive margin decision can be characterized by the choice of a constant soil moisture target for the entire growing season. Research has shown that the optimal level at which soil moisture should be maintained in fact differs intraseasonally [*Doorenbos and Kassam*, 1979; *Geerts and Raes*, 2009; *Payero et al*., 2009] as the degree of crop sensitivity to water stress varies according to crop phenology. Soil moisture target strategies that vary intraseasonally have been developed and modeled for a number of locations, including the High Plains Aquifer region [*Heeren et al*., 2011], but these strategies have yet to be incorporated into economic models of irrigation decision making. Whilst there is potential to extend the intensive margin decision of the modeling framework described in this study to incorporate these variable deficit irrigation strategies, it is not anticipated that this modification would significantly alter the optimality of predicted extensive margin adjustments. This assertion is supported by research indicating that the viability of deficit irrigation as an adaptation to limited water availability is predicated on the ability to supply irrigation to the crop at an unlimited rate during the most sensitive growth stages [*Fereres and Soriano*, 2007; *Geerts and Raes*, 2009]. Low well yields, which limit instantaneous irrigation application rates throughout the entire growing season, will therefore reduce the ability to manage soil moisture levels optimally during critical growth stages, resulting in adoption of extensive margin adjustments to increase potential instantaneous application rates and per-area crop yield and total profits. However, it should be noted that time-varying deficit irrigation strategies may allow farmers to adapt more effectively to regulatory groundwater supply restrictions. As regulatory constraints are imposed at an aggregate seasonal scale, deficit irrigation may enable farmers to prioritize the allocation of limited groundwater abstraction quotas to the most drought-sensitive crop growth stages while reducing applications and soil moisture levels at other points in the growing season. Consequently, optimal irrigated area and profits under regulatory groundwater supply restrictions may be larger than predicted by our model (Figure 5) provided that well yield is nonlimiting.

Finally, while the modeling framework developed is generalizable to different settings it should be noted that the exact quantitative model results are specific to the chosen case study. For example, the threshold at which well yield becomes a binding constraint on per-area crop yield and irrigated area size will vary according to a number of factors including climate, soil texture, crop type, crop price, and production costs. Sensitivity analyses (not shown here) for our model have demonstrated that the threshold level at which well yield becomes a binding constraint on irrigated area varies as a function of the difference between per-area crop price and production costs. When this difference is reduced relative to the values in Table 1, well yield becomes binding at higher pumping capacities as per-area revenue falls below per-area costs more rapidly. On the other hand, irrigated area can be maintained at higher levels for well yields below those predicted in this study when the difference between crop price and production costs is increased as the additional revenue per unit of crop yield is sufficient to mitigate some of the impacts of reduced crop yield as well yield declines. *Heeren et al*. [2011] have also shown in the High Plains region that the well yield threshold at which reductions in corn yields are expected, and at which irrigation decision making therefore may be affected, varies between around 600–800 gpm due to spatial variations in climate and soil type. In addition, farmer response to well yield decline will be influenced by the local context surrounding groundwater management. Our model assumes a farmer is unable to improve well yield (e.g., by drilling a deeper well). For the Ogallala Aquifer this is realistic as drilling of new wells generally is unfeasible due to well drilling moratoriums or because wells are already sunk at substantial depths. In other areas of the world farmers may be able to maintain irrigated area by drilling deeper wells to boost pumping capacity, and in these settings our model may need to be adapted to consider this additional component of economic decision making. However, it should be noted that drilling deeper wells may quickly become financially prohibitive for smallholder farmers [e.g., *Janakarajan and Moench*, 2006] and/or well yield gains may be restricted by geological constraints [e.g., *MacDonald et al*., 2012]. Furthermore, as exemplified by the historic expansion of well drilling in the Texas High Plains [*Colaizzi et al*., 2009], drilling increasingly deeper wells is likely simply to postpone the effects of declining well yields on irrigated area. Importantly, this discussion thus highlights that local variability in model parameters and institutional contexts will influence when, and not if, well yield becomes a binding constraint on irrigation decision making. The modeling framework developed in this paper therefore can be valuable for studying groundwater-fed irrigation across a wide range of settings.

5. Conclusions

This paper develops a behaviorally robust modeling framework for predicting optimal irrigation decision making. In contrast to existing approaches for predicting agricultural groundwater demand in integrated hydro-economic models, our model is consistent with the structure and variables that underlie farmers' actual field-level groundwater use decisions. Our novel stochastic intraseasonal crop-water production function explicitly accounts for both the intraseasonal structure of irrigation planning and the variability in this function induced by climate and well yield. The developed crop-water production function is applied within a realistic utility maximization framework, which is formulated to reflect the observation that farmers' must choose irrigated area preseason under uncertainty about future growing season conditions and water requirements.

The model is solved for a case study of center-pivot irrigated corn production in the Texas High Plains region of the United States to assess changes in irrigation behavior in response to groundwater supply restrictions and to understand the limits of applicability of existing crop-water production functions for predicting land and water use decisions by farmers. We find that optimal irrigation behavior exhibits complex nonlinear responses to reductions in groundwater supply. Most notably, instantaneous application rate constraints imposed by low well yields are shown to induce large reductions in the optimal size of irrigated area and, consequently, in expected field-level profitability. Existing model formulations are unable to capture these behavioral responses as they do not adequately account for the impacts on crop-water production decisions of intraseasonal supply constraints introduced by low well yields.

This study indicates that existing model formulations may not be robust predictors of irrigation decision making under conditions of constrained groundwater supply. Current research commonly suggests that the impacts of limited water availability on production area and profits can be mitigated largely through the adoption of deficit irrigation practices. Contrastingly, our results imply that a failure to account for increasing constraints on intraseasonal groundwater supply due to declining well yield will lead existing models to underestimate the negative impacts of groundwater depletion on potential food production and rural economies. This has important implications, suggesting that managing saturated thicknesses at levels necessary to preserve well yield may have significant additional economic and societal value that has been neglected in previous analyses. Finally, our results indicate that the nonlinear relationships between well yield and irrigated agricultural production may create a number of system thresholds that, once crossed, will rapidly magnify the potential damages incurred from groundwater depletion.

The analyses reported in this study represent a static, explicit prediction of the impacts of groundwater supply constraints on field-level irrigation decision making. However, in reality, the coupled human-water system is regulated at larger spatial scales and its components will dynamically coevolve over time, affecting the trajectory of changes in both the aquifer and agricultural production. An extension of our research could, in the spirit of the emerging field of socio-hydrology [*Sivapalan et al*., 2012], seek to couple the developed model of field-level irrigation decision making within a catchment scale hydrological model. Model coupling should be spatially explicit, considering diversity in crop, soil, and weather characteristics, along with the interactions between individual agents in space and time. Producer expectations with regard to crop yield returns and irrigation requirements, which currently are considered to be constant in our model, should also be allowed to evolve over time to capture the effects of knowledge accumulation and adaptive learning by farmers during the modeled planning horizon. Similarly, future work could also evaluate the value of information sources that are not currently accounted for in our model of farmer decision making, such as the role of weather forecasts to help schedule limited irrigation [*Gowing and Ejieji*, 2001; *Bergez and Garcia*, 2010; *Cai et al.*, 2011; *Hejazi et al.*, 2014], and how their effectiveness will be affected by constraints on groundwater supply related to well yield. The resultant coupled modeling framework would provide a useful tool for meaningful policy analysis, and would be especially relevant for efforts to balance future water and food production demands with long-term goals of hydrological sustainability.

Acknowledgments
The authors acknowledge the support of the Grantham Institute for Climate Change at Imperial College London, sponsor of the PhD research of T. Foster. This material is based upon work supported by USDA grant AG 2012-67003-19981 and by USDA-NIFA Hatch project ILLU-470-369.

References

Abedinpour, M., A. Sarangi, T. Rajput, M. Singh, H. Pathak, and T. Ahmad (2012), Performance evaluation of AquaCrop model for maize crop in a semi-arid environment, *Agric. Water Manage.*, *110*, 55–66, doi:10.1016/j.agwat.2012.04.001.
Alizadeh, H., and S. J. Mousavi (2013), Coupled stochastic soil moisture simulation-optimization model of deficit irrigation, *Water Resour. Res.*, *49*, 4100–4113, doi:10.1002/wrcr.20282.
Allen, R. G., L. S. Pereira, D. Raes, and Smith, M. (1998), Crop evapotranspiration—Guidelines for computing crop water requirements, *Irrig. Drain. Pap. 56*, Food and Agric. Organ. of the U. N., Rome.
Allen, R. G., I. A. Walter, R. L. Elliott, T. A. Howell, D. Itenfisu, M. E. Jensen, and R. L. Snyder (Eds.) (2005), *The ASCE Standardized Reference Evapotranspiration Equation*, 59 pp., Am. Soc. of Civ. Eng., Reston, Va.
Antle, J. M. (1983), Testing the stochastic structure of production: A flexible moment-based approach, *J. Bus. Econ. Stat.*, *1*(3), 192–201, doi:10.1080/07350015.1983.10509339.
Antle, J. M. (1987), Econometric estimation of producers' risk attitudes, *Am. J. Agric. Econ.*, *69*(3), 509–522, doi:10.2307/1241687.
Baumhardt, R., S. Staggenborg, P. Gowda, P. Colaizzi, and T. Howell (2009), Modeling irrigation management strategies to maximize cotton lint yield and water use efficiency, *Agron. J.*, *101*(3), 460–468, doi:10.2134/agronj2008.0041xs.
Bergez, J. E., and F. Garcia (2010), Is it worth using short-term forecasts for irrigation management?, *Eur. J. Agron.*, *33*(3), 175–181, doi:10.1016/j.eja.2010.05.003.
Brown, T. C., R. Foti, and J. A. Ramirez (2013), Projected freshwater withdrawals in the United States under a changing climate, *Water Resour. Res.*, *49*, 1259–1276, doi:10.1002/wrcr.20076.
Brozović, N., and R. Young (2014), Design and implementation of markets for groundwater pumping rights, in *Water Markets for the 21st Century: What Have We Learned?*, edited by K. Easter and Q. Huang, Springer, Dordrecht, in press.
Brozović, N., D. L. Sunding, and D. Zilberman (2010), On the spatial nature of groundwater pumping externality, *Resour. Energy Econ.*, *32*(2), 154–164, doi:10.1016/j.reseneeco.2009.11.010.
Brumbelow, K., and A. Georgakakos (2007), Consideration of climate variability and change in agricultural water resources planning, *J. Water Resour. Plann. Manage.*, *133*(3), 275–285, doi:10.1061/(ASCE)0733-9496(2007)133:3(275).
Bulatewicz, T., X. Yang, J. M. Peterson, S. Staggenborg, S. M. Welch, and D. R. Steward (2010), Accessible integration of agriculture, groundwater, and economic models using the Open Modeling Interface (OpenMI): Methodology and initial results, *Hydrol. Earth. Syst. Sci.*, *14*(3), 521–534, doi:10.5194/hess-14-521-2010.
Cai, X. (2008), Implementation of holistic water resources-economic optimization models for river basin management––Reflective experiences, *Environ. Modell. Software*, *23*(1), 2–18, doi:10.1016/j.envsoft.2007.03.005.
Cai, X., and D. Wang (2006), Calibrating holistic water resources-economic models, *J. Water. Res.*, *132*(6), 414–423, doi:10.1061/(ASCE)0733-9496(2006)132:6(414).
Cai, X., M. I. Hejazi, and D. Wang (2011), Value of probabilistic weather forecasts: Assessment by real-time optimization of irrigation scheduling, *J. Water Res.*, *137*(5), 391–403, doi:10.1061/(ASCE)WR.1943-5452.0000126.
Chavas, J. P. (2004), *Risk Analysis in Theory and Practice*, 247 pp., Elsevier Acad., San Diego, Calif.
Clark, G. A., and D. Rogers (2002), *KanSched: An ET-Based Scheduling Tool for Kansas Summer Annual Crops*, Kansas State Univ., Manhattan, Kans.
Colaizzi, P., P. Gowda, T. Marek, and D. Porter (2009), Irrigation in the Texas High Plains: A brief history and potential reductions in demand, *Irrig. Drain.*, *58*(3), 257–274, doi:10.1002/ird.418.
Crosbie, R. S., B. R. Scanlon, F. S. Mpelasoka, R. C. Reedy, J. B. Gates, and L. Zhang (2013), Potential climate change effects on groundwater recharge in the High Plains Aquifer, *USA, Water Resour. Res.*, *49*, 3936–3951, doi:10.1002/wrcr.20292.
Doorenbos, J., and A. H. Kassam (1979), Crop water requirements, *Irrig. Drain. Pap. 33*, Food and Agric. Organ. of the U. N., Rome.
Durre, I., M. J. Menne, B. E. Gleason, T. G. Houston, and R. S. Vose (2010), Comprehensive automated quality assurance of daily surface observations., *J. Appl. Meteorol. Clim.*, *49*(8), 1615–1633, doi:10.1175/2010JAMC2375.1.
Elliott, J., et al. (2013), Constraints and potentials of future irrigation water availability on agricultural production under climate change, *Proc. Natl. Acad. Sci. U. S. A.*, *111*(9), 3239–3244, doi:10.1073/pnas.1222474110.
English, M. (1990), Deficit irrigation. I: Analytical framework, *J. Irrig. Drain. Eng.*, *116*(3), 399–412, doi:10.1061/(ASCE)0733-9437(1990)116:3(399).
English, M. J., K. H. Solomon, and G. J. Hoffman (2002), A paradigm shift in irrigation management, *J. Irrig. Drain. Eng.*, *128*(5), 267–277, doi:10.1061/(ASCE)0733–9437(2002)128:5(267).
Evans, R. G., and E. J. Sadler (2008), Methods and technologies to improve efficiency of water use, *Water Resour. Res.*, *44*, W00E04, doi:10.1029/2007WR006200.
Fereres, E., and M. A. Soriano (2007), Deficit irrigation for reducing agricultural water use, *J. Exp. Bot.*, *58*(2), 147–159, doi:10.1093/jxb/erl165.
Finger, R. (2012), Modeling the sensitivity of agricultural water use to price variability and climate change—An application to Swiss maize production, *Agric. Water Manage.*, *109*, 135–143, doi:10.1016/j.agwat.2012.03.002.
García-Vila, M., and E. Fereres (2012), Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level, *Eur. J. Agron.*, *36*(1), 21–31, doi:10.1016/j.eja.2011.08.003.

Geerts, S., and D. Raes (2009), Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas, *Agric. Water Manage.*, *96*(9), 1275–1284, doi:10.1016/j.agwat.2009.04.009.

Geerts, S., D. Raes, M. Garcia, C. Taboada, R. Miranda, J. Cusicanqui, T. Mhizha, and J. Vacher (2009), Modeling the potential for closing quinoa yield gaps under varying water availability in the Bolivian Altiplano, *Agric. Water Manage.*, *96*, 1652–1658.

Gleeson, T., Y. Wada, M. F. Bierkens, and L. P. van Beek (2012), Water balance of global aquifers revealed by groundwater footprint, *Nature*, *488*(7410), 197–200, doi:10.1038/nature11295.

Gowing, J. W., and C. J. Ejieji (2001), Real-time scheduling of supplemental irrigation for potatoes using a decision model and short-term weather forecasts," *Agric. Water Manage.*, *47*(2), 137–153, doi:10.1016/S0378-3774(00)00101-3.

Harou, J. J., and J. R. Lund (2008), Ending groundwater overdraft in hydrologic-economic systems, *Hydrogeol. J.*, *16*(6), 1039–1055, doi:10.1007/s10040-008-0300-7.

Harou, J. J., M. Pulido-Velazquez, D. E. Rosenberg, J. Medellin-Azuara, J. R. Lund, and R. E. Howitt (2009), Hydro-economic models: Concepts, design, applications, and future prospects, *J. Hydrol.*, *375*(3-4), 627–643, doi:10.1016/j.jhydrol.2009.06.037.

Heeren, D. M., T. P. Trooien, H. D. Werner, and N. L. Klocke (2011), Development of deficit irrigation strategies for corn using a yield ratio model, *Appl. Eng. Agric.*, *27*(4), 605–614, doi:10.13031/2013.38207.

Hejazi, M. I., X. Cai, X. Yuan, X. Liang, and P. Kumar (2014), Incorporating reanalysis-based short-term forecasts from a regional climate model in an irrigation scheduling optimization problem, *J. Water Res.*, *140*(5), 699–713, doi:10.1061/(ASCE)WR.1943-5452.0000365.

Heng, L. K., T. Hsiao, S. Evett, T. Howell, and P. Steduto (2009), Validating the FAO AquaCrop model for irrigated and water deficient field maize, *Agron. J.*, *101*(3), 488–498, doi:10.2134/agronj2008.0029xs.

Hsiao, T. C., L. Heng, P. Steduto, B. Rojas-Lara, D. Raes, and E. Fereres (2009), AquaCrop––The FAO crop model to simulate yield response to water: III. Parameterization and testing for maize, *Agron. J.*, *101*(3), 448–459, doi:10.2134/agronj2008.0218s.

Itenfisu, D., R. L. Elliott, R. G. Allen, and I. A.Walter (2003), Comparison of reference evapotranspiration calculations as part of the ASCE standardization effort, *J. Irrig. Drain. Eng.*, *129*(6), 440–448, doi:10.1061/(ASCE)0733-9437(2003)129:6(440).

Janakarajan, S., and M. Moench (2006), Are wells a potential threat to farmers' well-being? Case of deteriorating groundwater irrigation in Tamil Nadu, *Econ. Polit. Weekly*, *41*(37), 3977–3987.

Jones, H. G. (2004), Irrigation scheduling: Advantages and pitfalls of plant-based methods, *J. Exp. Bot.*, *55*(407), 2427–2436, doi:10.1093/jxb/erh213.

Just, R. E., and R. D. Pope (1978), Stochastic specification of production functions and economic implications, *J. Econ.*, *7*(1), 67–86, doi:10.1016/0304-4076(78)90006-4.

Klocke, N., J. P. Schneekloth, S. R. Melvin, R. T.Clark, and J. O. Payero (2004), Field scale limited irrigation scenarios for water policy strategies, *Appl. Eng. Agric.*, *20*(5), 623–631, doi:10.13031/2013.17465.

Kloss, S., R. Pushpalatha, K. J. Kamoyo, and N. Schütze (2012), Evaluation of crop models for simulating and optimizing deficit irrigation systems in arid and semi-arid countries under climate variability, *Water Resour. Manage.*, *26*(4), 997–1014, doi:10.1007/s11269-011-9906-y.

Kranz, W. L., D. L. Martin, S. Irmak, S. J. van Donk, and D. C. Yonts (2008), *Minimum Center Pivot Design Capacitiesin Nebraska (G1851)*, Univ. of Nebr.-Lincoln Ext., Lincoln.

Kuwayama, Y., and N. Brozović (2013), The regulation of a spatially heterogeneous externality: Tradable groundwater permits to protect streams, *J. Environ. Econ. Manage.*, *66*(2), 364–382, doi:10.1016/j.jeem.2013.02.004.

Lamm, F., L. Stone, and D. O'Brien (2007), Crop production and economics in Northwest Kansas as related to irrigation capacity, *Appl. Eng. Agric.*, *23*(6), 737–746, doi:10.13031/2013.20754.

MacDonald, A. M., H. C. Bonsor, B. E. O. Dochartaigh, and R. G. Taylor (2012), Quantitative maps of groundwater resources in Africa, *Environ. Res. Lett.*, *7*(2), 024009, doi:10.1088/1748-9326/7/2/024009.

Maneta, M. P., M. O. Torres, W. W. Wallender, S. Vosti, R. Howitt, L. Rodrigues, L. H. Bassoi, and S. Panday (2009), A spatially distributed hydroeconomic model to assess the effects of drought on land use, farm profits, and agricultural employment, *Water Resour. Res.*, *45*, W11412, doi:10.1029/2008WR007534.

Marek, T., et al. (2013), *2012 North Plains Research Field 12-200 Limited Irrigation Corn Production Study*, Texas A&M AgriLife Res., Amarillo.

Mathworks Inc. (2013), *Matlab Release 2013b*, 8.2.0.701 ed., Natick, Mass.

McGuire, V. L., K. D. Lund, and B. K. Densmore (2012), Saturated thickness and water in storage in the high plains aquifer, 2009, and water-level changes and changes in water in storage in the High Plains Aquifer, 1980 to 1995, 1995 to 2000, 2000 to 2005, and 2005 to 2009, *U.S. Geol. Surv. Sci. Invest. Rep. 2012-5177*, U.S. Geol. Surv., Reston, Va.

Mebane, V. J., R. L. Day, J. M. Hamlett, J. E. Watson, and G. W. Roth (2013), Validating the FAO AquaCrop Model for Rainfed Maize in Pennsylvania, *Agron. J.*, *105*(2), 419–427, doi:10.2134/agronj2012.0337.

Nair, S., S. Maas, C. Wang, and S. Mauget (2013), Optimal field partitioning for center-pivot-irrigated cotton in the Texas high plains, *Agron. J.*, *105*(1), 124–133, doi:10.2134/agronj2012.0219.

National Agricultural Statistics Service (2008), *2007 Census of Agriculture. Farm and Ranch Irrigation Survey. Volume 3. Special Studies Part 1. AC-07-SS-1*, United States Department of Agriculture National Agricultural Statistics Service, Washington, D. C.

National Agricultural Statistics Service (2010), *Field Crops. Usual Planting and Harvest Dates*, United States Department of Agriculture National Agricultural Statistics Service, Washington, D. C.

New, L., and G. Fipps (2002), *Center Pivot Irrigation*, Tex. Agric. Ext. Serv., College Station.

O'Brien, D., F. Lamm, L. Stone, and D. Rogers (2001), Corn yields and profitability for low-capacity irrigation systems, *Appl. Eng. Agric.*, *17*(3), 315–321, doi:10.13031/2013.6217.

Payero, J. O., D. D. Tarkalson, S. Irmak, D. Davison, and J. L. Petersen (2009), Effect of timing of a deficit-irrigation allocation on corn evapotranspiration, yield, water use efficiency and dry mass, *Agric. Water Manage.*, *96*(10), 1387–1397, doi:10.1016/j.agwat.2009.03.022.

Peterson, J. M., and Y. Ding (2005), Economic adjustments to groundwater depletion in the high plains: Do water-saving irrigation systems save water?, *Am. J. Agric. Econ.*, *87*(1), 147–159, doi:10.1111/j.0002-9092.2005.00708.x.

Raes, D., P. Steduto, T. C. Hsiao, and E. Fereres (2012), *AquaCrop Version 4.0 Reference Manual*, FAO Land and Water Div., Rome.

Rodell, M., I. Velicogna, and J. S. Famiglietti (2009), Satellite-based estimates of groundwater depletion in India, *Nature*, *460*(7258), 999–1002, doi:10.1038/nature08238.

Rosegrant, M. W., X. Cai, and S. A. Cline (2002), *World Water and Food to 2025: Dealing with Scarcity*, Int. Food Policy Res. Inst., Washington, D. C.

Sauer, T., P. Havlík, U. A. Schneider, E. Schmid, G. Kindermann, and M. Obersteiner (2010), Agriculture and resource availability in a changing world: The role of irrigation, *Water Resour. Res.*, *46*, W06503, doi:10.1029/2009WR007729.

Saxton, K. E., W. J. Rawls, J. S. Romberger, and R. I. Papendick (1986), Estimating generalized soil-water characteristics from texture, *Soil Sci. Soc. Am. J.*, *50*(4), 1031–1036, doi:10.2136/sssaj1986.03615995005000040039x.

Scanlon, B. R., C. C. Faunt, L. Longuevergne, R. C. Reedy, W. M. Alley, V. L. McGuire, and P. B. McMahon (2012), Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley, Proc. Natl. Acad. Sci. U. S. A., *109*(24), 9320–9325, doi:10.1073/pnas.1200311109.

Schewe, J., et al. (2013), Multimodel assessment of water scarcity under climate change, *Proc. Natl. Acad. Sci. U. S. A.*, doi:10.1073/pnas.1222460110.

Schoups, G., C. L. Addams, J. L. Minjares, and S. M. Gorelick (2006), Sustainable conjunctive water management in irrigated agriculture: Model formulation and application to the Yaqui Valley, Mexico, *Water Resour. Res.*, *42*, W10417, doi:10.1029/2006WR004922.

Schütze, N., and G. Schmitz (2010), OCCASION: New planning tool for optimal climate change adaption strategies in irrigation, *J. Irrig. Drain. Eng.*, *136*(12), 836–846, doi:10.1061/(ASCE)IR.1943-4774.0000266.

Shani, U., Y. Tsur, and A. Zemel (2004), Optimal dynamic irrigation schemes, *Optim. Control Appl. Methods*, *25*(2), 91–106, doi:10.1002/oca.740.

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

Smith, M. (1992), *CROPWAT: A Computer Program for Irrigation Planning and Management*, Food & Agric. Organ. of the U. N., Rome.

Steduto, P., T. C. Hsiao, and E. Fereres (2007), On the conservative behavior of biomass water productivity, *Irrig. Sci.*, *25*(3), 189–207, doi:10.1007/s00271-007-0064-1.

Steduto, P., T. C. Hsiao, D. Raes, and E. Fereres (2009), AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles, *Agron. J.*, *101*(3), 426–437, doi:10.2134/agronj2008.0139s.

Steward, D. R., P. J. Bruss, X. Yang, S. A. Staggenborg, S. M. Welch, and M. D. Apley (2013), Tapping unsustainable groundwater stores for agricultural production in the High Plains Aquifer of Kansas, projections to 2110, Proc. Natl. Acad. Sci. U. S. A., *110*(37), E3477–E3486, doi:10.1073/pnas.1220351110.

Stricevic, R., M. Cosic, N. Djurovic, B. Pejic, and L. Maksimovic (2011), Assessment of the FAO AquaCrop model in the simulation of rainfed and supplementally irrigated maize, sugar beet and sunflower, *Agric. Water Manage.*, *98*(10), 1615–1621, doi:10.1016/j.agwat.2011.05.011.

Texas AgriLife Extension Service (2013), *Estimated Costs and Returns Per Acre. Corn for Grain, Pivot Irrigated—Herbicide-Tolerant, Insect-Resistant (D2)*, Texas A&M AgriLife Ext., College Station.

Texas Water Development Board (2001), Surveys of irrigation in Texas, 1958, 1964, 1969, 1974, 1979, 1984, 1989, 1994, and 2000, *Rep. 347*, Austin, Tex.

Texas Water Development Board (2012), *2012 Water for Texas*, Austin, Tex.

Varela-Ortega, C., I. Blanco-Gutiérrez, C. H. Swartz, and T. E. Downing (2011), Balancing groundwater conservation and rural livelihoods under water and climate uncertainties: An integrated hydro-economic modeling framework, *Global Environ. Change*, *21*(2), 604–619, doi:10.1016/j.gloenvcha.2010.12.001.

Vico, G., and A. Porporato (2011), From rainfed agriculture to stress-avoidance irrigation: I. A generalized irrigation scheme with stochastic soil moisture, *Adv. Water Resour.*, *34*(2), 263–271, doi:10.1016/j.advwatres.2010.11.010.

Wada, Y., L. P. H. van Beek, and M. F. P. Bierkens (2012), Nonsustainable groundwater sustaining irrigation: A global assessment, *Water Resour. Res.*, *48*, W00L06, doi:10.1029/2011WR010562.

Wagner, K. (2012), *Status and Trends of Irrigated Agriculture in Texas*, Texas A&M AgriLife Res., Amarillo, Tex.

Wang, C., and S. Nair (2013), The economics of deficit irrigation, *Nat. Resour. Modell.*, *26*(3), 331–364, doi:10.1111/nrm.12004.

Wang, D., and X. Cai (2007), Optimal estimation of irrigation schedule—An example of quantifying human interferences to hydrologic processes, *Adv. Water Resour.*, *30*(8), 1844–1857, doi:10.1016/j.advwatres.2007.02.006.

Wines, M. (2013), Wells dry, fertile plains turn to dust, *New York Times*, A1 pp. [Available at http://www.nytimes.com/2013/05/20/us/high-plains-aquifer-dwindles-hurting-farmers.html?pagewanted=all&_r=0.]

