Why well yield matters for managing agricultural drought risk

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Abstract

Groundwater-fed irrigation has supported growth in agricultural production around the world by allowing farmers to buffer production against the risks associated with variable and uncertain climatic conditions. However, uncontrolled exploitation has also led to rapid rates of groundwater depletion in many semi-arid and arid regions that threaten farmers’ long-term capacity to adapt to future climate change and extreme events. Declining well yields, which control the potential rate and feasibility of groundwater abstraction, are likely to restrict adaptation to drought, but this interaction has largely been neglected in previous research. In this study, we present a set of numerical hydro-economic simulations that assess the joint biophysical and economic effects of climate variability and well yield on irrigated agriculture through a case study in the Texas High Plains region of the United States. Our results demonstrate that reductions in well yield will constrain farmers’ ability to use irrigation as an adaptive tool, and may have large negative economic impacts on production. Significantly, economic impacts will be greatest during drought events that are projected to increase in frequency and intensity as a result of climate change. We suggest therefore that management of well yields should be a key consideration when evaluating agricultural drought risk adaptation.

1. Introduction

Groundwater provides a reliable, high quality, and accessible source of freshwater that enables farmers to mitigate against the production risks associated with extreme weather events and climate variability. Globally, over 300 million ha of agricultural land is irrigated using groundwater (FAO, 2011), supporting crop and food production systems with an estimated annual economic value of $210–230 billion (Shah et al., 2007). However, the development of groundwater resources for irrigation often results in total abstraction rates exceeding long-term natural rates of groundwater replenishment. As a result, declining aquifer storage volumes and water tables can be observed in regions of intensive agricultural production, such as the High Plains of the United States (Scanlon et al., 2012; Breña-Naranjo et al., 2014).

Alongside concerns about the sustainability of current rates of groundwater use, there is also increasing recognition of the potential impacts that future climate change may have on demand for groundwater from irrigated agriculture (Taylor et al., 2013). High levels of uncertainty exist in projections of future irrigation water demands. Uncertainty arises from a number of sources, including, most notably, the choice of greenhouse gas emission trajectory, projections of spatial and temporal changes in precipitation patterns, and the potential influence of elevated CO₂ concentrations on crop water use efficiency (Wada et al., 2013). Nevertheless, there is agreement that higher temperatures, and resultant increases in potential evapotranspiration rates, will raise both total and peak irrigation water requirements over much of the global agricultural land area (Döll and Siebert, 2002; Konzmann et al., 2013; Wada et al., 2013; Elliott et al., 2014). Furthermore, there is consensus that the intensity and frequency of temperature and precipitation extremes are likely to increase in the future as a result of warming to the climate system (Dai, 2011; Intergovernmental Panel on Climate Change, 2012). These extreme events, such as heat waves and droughts, in themselves may have large negative impacts on crop productivity and would be expected to increase depletion of groundwater by both agriculture and other sectors (Famiglietti et al., 2011; Scanlon et al., 2012; Long et al., 2013; Castle et al., 2014).

Declining groundwater availability, coupled with climate variability and change, may have significant ramifications for farmers’ ability to continue to manage production risks and deliver food security. Despite this, currently there is limited understanding of the joint effects of climate and groundwater availability on the productivity and profitability of irrigated agriculture. Integrated hydro-economic modelling has been extensively used to evaluate sustainable groundwater management and the
consequences of reductions in aquifer storage volumes for irrigated agriculture (e.g., Bulatiewicz et al., 2010; Steward et al., 2013; Mulligan et al., 2014). However, hydro-economic models commonly assume that the relationship between crop yield and seasonal applied irrigation is constant temporally, and, therefore, are unable to address the effects of interannual weather variability on farmers’ optimal irrigation decision making under conditions of changing groundwater availability. Moreover, changes in groundwater storage may not represent the most important consequence of aquifer depletion for farmers’ ability to mitigate the effects of variable climate. Changes in well yields, the upper limit on the volumetric rate of groundwater abstraction, that are a non-linear function of aquifer saturated thickness have been shown to have large impacts on crop yields and optimal irrigation decision making (Peterson and Ding, 2005; Lamm et al., 2007; Foster et al., 2014, 2015). Foster et al. (2014) develop a methodology for incorporating well yield constraints on groundwater availability into integrated hydro-economic modelling of irrigated agriculture. However, Foster et al. (2014) analyse the average impacts of well yield on groundwater-fed irrigated agriculture and do not evaluate explicitly the importance of well pumping capacity for managing drought risk.

In this paper, we apply the biophysical crop simulation model AquaCrop (Steduto et al., 2009) within a refined version of the hydro-economic modelling framework developed by Foster et al. (2014) in order to evaluate the effect of well yield on groundwater-fed irrigated agriculture under a range of specific weather conditions. We focus our analyses on a case study of centre-pivot irrigated corn production in the Texas High Plains in the United States, a region where substantial groundwater depletion has occurred (Scanlon et al., 2012) and where agricultural production has also been negatively affected by severe drought events in recent years (Fannin, 2012; Long et al., 2013). Our results demonstrate that high yielding wells may play an important role in buffering farmers against the negative effects of drought conditions. This finding suggests that, in many areas of the world, ongoing groundwater depletion, and its potential impacts on well yields, may act to magnify the impacts of future climate change on agriculture, with implications for long-term food security and the sustainability of rural economies.

2. Methodology

2.1. Crop simulation model

The biophysical crop simulation model AquaCrop is used as the basis for estimating the joint impacts of well yield and weather conditions on irrigation decision making, and the economic value that irrigation generates. AquaCrop is a water-limited crop yield model that was originally developed by the Food and Agriculture Organization of the United Nations, and that has since been recoded into the Matlab programming language (Mathworks Inc., 2013) to facilitate rapid integration in multi-disciplinary modelling frameworks (Foster et al., 2014). We choose AquaCrop as the basis for simulating the effects of weather variability on crop production in our model for a number of reasons. First, AquaCrop simulates crop yield using a water-driven growth engine that has been designed to capture explicitly the effects of water stress on key crop processes such as canopy growth and senescence, stomatal conductance, and pollination (Raes et al., 2009; Steduto et al., 2009; Vanuytrecht et al., 2014). In addition, while other crop simulation models also are capable of simulating water stress impacts on crop growth and yield development, AquaCrop has substantially lower computational requirements for model parameterization that make it ideally suited for use within the integrated modelling framework that is proposed in this study. Moreover, this simplicity does not compromise model performance, as illustrated by the diverse range of studies around the world that have shown that AquaCrop is able to simulate accurately corn production under different levels of water stress (Heng et al., 2009; Hsiao et al., 2009; Strievic et al., 2011; Abedinpur et al., 2012; Garcia-Vila and Fereres, 2012; Mebane et al., 2013; Paredes et al., 2014).

For the simulations presented in this study, we parameterize AquaCrop to be representative of typical centre-pivot irrigated corn production conditions in the Texas High Plains region of the United States. Crop growth parameters are set equal to the values obtained from a previous validation of AquaCrop at Bushland in the Texas High Plains (Heng et al., 2009) that has demonstrated that AquaCrop is able to effectively reproduce corn growth and yield across a range of irrigation conditions ranging from rainfed to full irrigation. Soil type in AquaCrop is defined as a Sherrm silty clay loam soil, which has textural properties of 23% sand, 46% clay, and an organic matter content of 0.66% as reported in the SSURGO soils database (U.S. Department of Agriculture Natural Resources Conservation Service, 2015). This soil type was chosen based on a comparison of the soils data reported in the SSURGO dataset (U.S. Department of Agriculture Natural Resources Conservation Service, 2015) and historic crop production areas given in the CropScape dataset (U.S. Department of Agriculture National Agricultural Statistics Service, 2015), which show that Sherrm silty clay loam soils represent one of the most common soil types for irrigated crop production in the Texas High Plains region (Foster et al., 2014). A pedotransfer function model (Saxton and Rawls, 2006) is used to translate these textural characteristics into estimates of the soil hydraulic properties used in AquaCrop, yielding water contents at saturation, field capacity, and permanent wilting point of 0.483, 0.406, and 0.274 m3 m−3, respectively, and a saturated hydraulic conductivity of 27 mm day−1. Further information on crop, soil, and irrigation management parameters used in these simulations is provided in Foster et al. (2014).

Weather data required by AquaCrop are obtained from the National Oceanic and Atmospheric Association Global Summary of the Day data set (U.S. National Climatic Data Center, 2014) for a weather station located at Rick Husband International Airport in Amarillo, Texas. This dataset contains records of daily weather inputs needed by AquaCrop (maximum and minimum temperature, and total precipitation) along with other variables (dew point temperature and mean wind speed) for the years 1943–2013. 55 of these 71 years are used in the biophysical simulations as the other 16 years contain substantial missing values and/or data errors. The final input required by AquaCrop, daily reference evapotranspiration, is estimated using the standardized American Society of Civil Engineers (ASCE) Penman–Monteith equation (Allen et al., 2005) that has been shown to predict accurately reference evapotranspiration for climatic conditions in the Texas High Plains (Itenfisu et al., 2003). The 55-year weather time series captures the range of potential weather conditions that typically are experienced by producers in the Texas High Plains. Between the specified planting date of May 1 and a common harvest date of October 1 (U.S. Department of Agriculture, 2010), total precipitation ranges from 81 mm in the driest year in the record (2011) to 650 mm in the wettest year (1960) with an average value of 353 mm. Similarly, there is also large interannual variability in the total reference evapotranspiration, which ranges from a low of 914 mm (1949) to a high of 1452 mm (2011) with an average seasonal total of 1101 mm. Importantly, the variability in this historic weather record enables quantification of the effects of interannual weather variability on crop yield returns to irrigation as will be discussed further in Section 2.2.
2.2. Simulation of the crop-water production function

We use AquaCrop to simulate the relationships between the choice of an intraseasonal soil moisture target, equal to a specified proportion of soil water holding capacity within the crop root zone at which irrigation is initiated on any given day during the growing season, and both final crop yield and total irrigation requirements. These simulations use the stochastic intraseasonal formulation of the crop-water production function that is developed in Foster et al. (2014) (Eq. (1)), and assume that the soil moisture target varies from 0 (equal to permanent wilting point) to 1 (equal field capacity) in steps of 0.05. Simulations are iteratively repeated for each of the 55 years of weather data, \( \Theta_t \), and also consider a range constraints on the maximum daily irrigation rate, \( x_{\text{max}} \), ranging from 0.1 mm day\(^{-1}\) to 20 mm day\(^{-1}\) in increments of 0.1 mm day\(^{-1}\). On each day of each simulation, irrigation is triggered in AquaCrop if the simulated root zone soil moisture content is below the specified soil moisture target threshold. We make the assumption in our model that irrigation is applied at a uniform daily rate across the entire irrigated area in order to raise the soil water content towards field capacity, subject to the specified constraint on the maximum daily irrigation application depth. Consequently, we do not consider a farmer’s capacity to maintain higher instantaneous irrigation rates by choosing to irrigate the total field area over a period of multiple days. This assumption reflects the fact that AquaCrop, along with most other crop models, typically are applied on a uniform per-area basis due to the significant computational and technical burden associated with tracking within-field variability in soil water dynamics and crop growth processes. Nevertheless, it is important to note that, if the uniform irrigation rate on a given day is insufficient to raise soil moisture content above the target threshold, additional irrigation will be applied on subsequent days of the simulation to further supplement soil water storage:

\[
\begin{align*}
Y_t &= f(x_{t-1}^{1-\xi_t}, \Theta_t^{1-\xi_t}) \\
X_t &= \sum_{i=1}^{n_t} x_i^{(t)} = f(S, \Theta_t^{1-\xi_t}) \\
\text{subject to :} \\
0 \leq x_i^{(t)} &\leq x_{\text{max}} \\
x_{\text{max}} &= C \cdot \frac{W}{A}
\end{align*}
\]

(1)

where \( Y_t \) and \( X_t \) are the crop yield (tonne ha\(^{-1}\)) and total per-area depth of applied irrigation (mm yr\(^{-1}\)), respectively, in year \( t \), \( x_i \) and \( \Theta_t \) are vectors of daily per-area irrigation application depths (mm day\(^{-1}\)) and weather inputs, respectively, in year \( t \) of length \( n_t \), \( n_t \) is the number of days in the growing season in year \( t \) that is determined by AquaCrop as function of the accumulation of growing degree days after planting and the specified input crop phenological calendar, \( x_{\text{max}} \) is the maximum daily irrigation depth (mm day\(^{-1}\)), \( W \) is the well yield (m\(^3\) day\(^{-1}\)), \( A \) is the irrigated area (ha), \( S \) is the intraseasonal soil moisture target, and \( C \) is a unit conversion factor.

For each potential value of \( x_{\text{max}} \), the 55 years of simulated data points describing the stochastic relationship between the intraseasonal soil moisture target and both final crop yield and total seasonal irrigation are aggregated to create data points of crop yield as a function of total seasonal applied irrigation. After interpolating the irrigation-yield relationship for each year using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) function in MATLAB (Mathworks Inc., 2013), percentiles of the stochastic crop-water production function are then computed to characterize the crop-water production function under a range of different prevailing climatic conditions. Each percentile of the crop-water production does not correspond directly to the weather in any specific individual year of the 55-year historic record used to simulate Eq. (1). However, in general, the lower percentiles are characteristic of years that are hotter and drier, whereas the higher percentiles are representative of wetter years with less frequent extreme heat events that can negatively impact crop growth. In turn, the 50th percentile is characteristic of the typical median crop-water production relationship under average climatic conditions observed historically in the region. This method is comparable to the approach used by Schütze and Schmitz (2010) to characterize the stochastic nature of the crop-water production function. However, Schütze and Schmitz (2010) optimize the intraseasonal scheduling of total seasonal irrigation, and also do not impose an upper limit on daily irrigation rates in their analysis. The percentile crop-water production functions generated by Schütze and Schmitz (2010) therefore implicitly assume perfect foresight of weather conditions in every growing season and do not account for the effects of limited instantaneous irrigation capacity that may affect irrigation decision making in groundwater systems. This assumption is likely to lead to overestimates of crop yield return to seasonal irrigation using groundwater. Contrastingly, the methodology used here makes a more realistic assumption that decisions on when to irrigate and how much water to apply are made solely on the basis of the current state of soil moisture and available well pumping capacity (Foster et al., 2014).

Fig. 1 shows the generated percentile crop-water production functions, and how each percentile function varies for three selected maximum daily irrigation rates (5 mm, 10 mm, and 20 mm). Fig. 1 demonstrates the impact of interannual weather variability on the crop-water production function, illustrating that crop yields are reduced for lower percentiles of the stochastic production relationship, which reflect crop production in drier years that are less favourable for crop growth. In addition, the maximum attainable irrigated crop yield is reduced at lower percentiles of the production function, highlighting that AquaCrop is capable of capturing the negative impacts of extreme heat events on corn yield (Lobell et al., 2013). Furthermore, it is evident that reductions in the maximum daily irrigation rate, in particular below 10 mm day\(^{-1}\), may lead to additional reductions in crop water productivity that may amplify the effect of extreme weather events on crop production returns to irrigation. Specifically, for a given level of total seasonal irrigation, crop yield declines as maximum daily irrigation rates are reduced because the farmer increasingly is unable to satisfy crop water requirements fully throughout the growing season, leading to the build-up of soil moisture deficits and resultant reductions in final crop yields. It is also important to note that the impacts of limited intraseasonal irrigation capacity are variable depending on climatic conditions. Fig. 1a demonstrates that in average or wet years the reduction in crop yields may be relatively small, so long as the farmer is able to increase total seasonal irrigation use to enable more frequent, but less intense, irrigation during the growing season. Contrastingly, in drier years, crop yield return to irrigation may be significantly reduced as intraseasonal irrigation supply is insufficient to avoid damaging water stress impacts on crop growth and yield development.

2.3. Estimation of optimal irrigation decision making

The generated crop-water production functions are used to evaluate the joint effect of weather conditions and well yield on economically optimal field-level irrigation decision making. Well yield is assumed to vary from 0 m\(^3\) day\(^{-1}\) to 10,000 m\(^3\) day\(^{-1}\) in increments of 100 m\(^3\) day\(^{-1}\). Variability in weather conditions is characterized by selecting different percentiles of the crop-water development.
production function, from 10% to 90% in steps of 10%, where lower percentiles represent production in drier, hotter years, and higher percentiles reflect production in wetter years with limited damaging extreme heat events. For each combination of well yield and the percentile crop-water production function, the expected profit and profit-maximizing per-area irrigation use are calculated for each potential choice of irrigated area size using Eq. (2). In this numerical case study, irrigated area size is allowed to vary from 0 ha to 52.65 ha in increments of 0.405 ha, which is characteristic of a typical centre-pivot irrigation system used in the Texas High Plains that can irrigate a total area of 52.65 ha. Economic parameter values used in Eq. (2) are taken from Texas AgriLife Extension Service (2013) and are summarized in Table 1:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop price ($ tonne⁻¹)</td>
<td>216.52</td>
</tr>
<tr>
<td>Fixed costs ($ ha⁻¹)</td>
<td>1285.07</td>
</tr>
<tr>
<td>Variable water costs ($ ha-mm⁻¹)</td>
<td>0.94</td>
</tr>
<tr>
<td>Variable harvest costs ($ tonne⁻¹)</td>
<td>15.75</td>
</tr>
</tbody>
</table>

Given the calculated optimal irrigated area, the optimal expected profit and volumetric irrigation use for each combination of well yield and production function percentile are then set equal to the values calculated in Eq. (2). In these analyses the non-irrigated portion of the field has no value, and the farmer is assumed not to adjust crop type or variety (i.e. corn is the only choice available). Consequently, predictions reflect the joint weather and well yield impacts on irrigated corn production, but probably represent a lower bound on the overall adaptive capacity for farmers who are able to diversify production, either fully or partially, to dryland agriculture or a less water intensive crop type when faced with limited well yield and/or drought conditions.

2.4. Sensitivity analysis

The generation of crop-water production functions, and subsequent estimation of optimal irrigation decision making, described in the previous sections are conditioned on the assumption that soil water content at the start of any growing season is equal to 100% of soil water holding capacity (i.e. field capacity). This high soil moisture level is characteristic of years in which a reasonable amount of rainfall occurs in the spring before the start of growing season, or of years when the farmer begins to apply irrigation before the start of the growing season in order to increase soil water availability for crop growth. However, at the start of the next growing season following the end of a period of drought, during prolonged multi-year drought events, or when a farmer does not carry out any irrigation before the beginning of the growing season, the soil water content at planting may be significantly lower than field capacity (Grassini et al., 2010). Importantly, water stored in the soil before the crop is planted provides a source of water supply, in addition to rainfall and irrigation that occurs during the growing season itself, which can be used to meet crop water requirements. Depletion of this initial soil water store may increase demand for groundwater-fed irrigation and exacerbate the vulnerability of farmers with low well yields to drought conditions during the growing season.

To account for the sensitivity of model predictions to the initial soil water content, the percentile crop-water production functions are re-generated by repeating the biophysical simulations described in Section 2.2 with initial soil water content in AquaCrop...
set equal to 75%, 50%, or 25% of soil water holding capacity. These production functions are then applied in turn to simulate optimal irrigation decision making for each combination of well yield and percentile crop-water production function, as described in Section 2.3, and the results compared to those obtained when an initial soil water content of 100% of soil water holding capacity is assumed in the generation of the percentile crop-water production functions.

3. Results and discussion

3.1. Optimal irrigation strategies

Fig. 2 illustrates the simulated relationship between optimal irrigated area and well yield for different percentiles of the crop-water production function. As has been highlighted previously by Foster et al. (2014), irrigated area exhibits a nonlinear declining trend with reductions in well yield due to the constraints that low well yields impose on instantaneous irrigation rates and the resultant negative impacts on per-area crop yields if irrigated area is not reduced in order to relax the constraint on the per-area daily irrigation rate. However, Fig. 2 demonstrates that this response of irrigated area to well yield is also highly sensitive to prevailing weather conditions during the growing season. The range of well yields over which it is optimal to irrigate the full 52.65 ha field area is substantially smaller for low percentiles of the crop-water production function, which are indicative of production during growing seasons with below average precipitation, than for higher percentiles of the crop-water production that are representative of growing seasons with more favourable weather conditions. Indeed, the threshold below which irrigated area becomes limited by well yield is around 8900 m$^3$ day$^{-1}$ for the 90th percentile of the crop-water production compared to a threshold that is as low as 1900 m$^3$ day$^{-1}$ for the 90th percentile of the crop-water production function. This difference reflects the fact that in drought years, lower growing season precipitation and higher evapotranspiration demands mean larger well pumping capacities are required in order to maintain soil moisture at levels that avoid negative water stress effects on crop growth and yield formation. As it is not feasible to increase well yield, an assumption that is realistic in the Texas High Plains where most wells and pumps have already been extended to extract groundwater from substantial depths, during drought years our model suggests that it would be economically optimal for a farmer to reduce the area of irrigated crops that is planted in order to increase per-area intraseasonal irrigation supply to levels that mitigate effectively the risk of severe crop failure. Nevertheless, it is important to note that the results discussed above are predicated on the assumption in our model that the farmer knows the percentile of the crop-water production, and, hence, has knowledge about how dry or wet the upcoming growing season is likely to be. In practice, a farmer may have only imperfect information about expected growing conditions. Given the large effect that expected weather has on optimal irrigated area, in particular for farmers with low-yielding wells, our results indicate that uncertainty about expected weather conditions therefore may lead farmers to plant irrigated crop areas that are sub-optimal for their available well pumping capacity with consequent reductions in farm profitability. Moreover, this also suggests that reliable information about the likelihood of drought, for example from improved seasonal climate forecasts, may be useful to help farmers to maximize the value of groundwater-fed irrigation in regions where well yields are declining.

Patterns of volumetric irrigation use are also strongly influenced by the interaction of well yield and weather conditions. Fig. 3 shows that irrigation use increases with declines in the percentiles of the crop-water production function when well yield is at, or close to, the maximum value modelled. Logically, this indicates that a farmer will use more irrigation in drier years where precipitation is below average and evapotranspiration demands are high. As well yield is reduced below around 9000 m$^3$ day$^{-1}$ volumetric irrigation use starts to decline due to the constraints imposed on intraseasonal groundwater availability. It is noticeable that declines in irrigation use occur first for the lowest percentiles of the crop-water production and, as a result, a range of well yields appears to exist where optimal volumetric irrigation use is larger in wetter years (higher percentiles of the crop-water production function) than in drier years (lower percentiles of the crop-water production function). This paradoxical result is a direct consequence of the trends in irrigated area observed in Fig. 2, which show that irrigated area declines more rapidly with reductions in well yield in drought years than it does in wetter years. The changes in volumetric irrigation use shown in Fig. 3 are dominated by these trends in irrigated area and, therefore, reflect the combined impacts of growing season weather conditions and well yield on irrigation decision making. Contrastingly, reductions in per-area irrigation application rates make up only a small proportion of the changes in volumetric irrigation use in Fig. 3. The minimal changes in per-area irrigation rates reflect the fact that...
irrigation demand for the 90th percentile production function is due to the large reductions in irrigated area that occur across almost the entire range of well pumping capacities that are modelled in this analysis (Fig. 2). Contrastingly, more gradual reductions in profits occur under more favourable weather conditions as the threshold at which well yield is a binding constraint on irrigated area is lower. This result suggests that to avoid severe negative economic impacts from drought events, such as the estimated $7.62 billion losses that occurred during the 2011 drought in the Texas High Plains (Fannin, 2012), farmers are likely to be highly dependent on access to productive wells that are becoming increasingly scarce as a result of continued depletion of groundwater resources.

Finally, it is important to reiterate that, as discussed in Section 3.1, predictions of expected profitability are conditioned on the assumption that the farmer knows which percentile of the crop-water production function will characterize weather conditions for the upcoming growing season. While in this paper we do not model explicitly the effects on irrigation decision making of uncertainty about expected weather conditions, we hypothesize that a farmer with imperfect information about expected weather is likely to make irrigation choices that are sub-optimal. For example, a farmer who plants the maximum irrigated area in expectation of a wet growing season may incur significant economic losses if the season is characterized by drought conditions that result in crop failure due to insufficient well pumping capacity. Similarly, a farmer who expects a drought to occur is likely to make planting decisions that are overly conservative if the growing season turns out to be more favorable for crop production. As a result, in situations where information about future weather conditions is unavailable or uncertain then actual farm profits may be lower than predicted by our model unless losses are underwritten, for example by some form of crop insurance.

3.3. Influence of initial soil water content

At the start of the growing season, the amount of water that is stored in the soil and available to support crop growth may be highly variable depending on hydrological conditions before the time of crop planting. In the analyses presented previously, it has been assumed that the entire soil profile is wetted fully to field capacity at the start of each growing season, but, in practice, soil water content when the crop is planted may be lower than this. Lower initial soil water storage may occur if drought events extend for multiple years, or if there is insufficient rainfall or supplemental irrigation applied to the soil before the start of the growing season. As a result, it is important to assess how farmers’ optimal irrigation decision making, and its sensitivity to well yield, is influenced by variable initial soil water storage. Fig. 5 illustrates how varying the initial soil water content value between 25% and 100% of soil water holding capacity affects the response of optimal irrigation area to well yield for three different percentiles of the crop-water production function that span a range of potential weather conditions: (a) 10th percentile, (b) 50th percentile, and (c) 90th percentile.

Fig. 5 shows that, irrespective of growing season weather conditions, depletion of soil moisture before the crop is planted results in further extensive margin adjustments to the optimal size of irrigated area. In both average (Fig. 5b) and wet (Fig. 5c) growing seasons, higher initial soil water contents are shown to reduce the sensitivity of farmers’ irrigated area choice to reductions in well yields. Even more striking is the effect in dry years (Fig. 5a), where an increase in the initial soil water content from 25% to 50% of soil water holding capacity provides sufficient additional water to determine whether or not irrigated production is optimal economically for the farmer across the entire range of well yields that are modelled. These results are indicative of the fact that stored soil moisture at the start of the growing season

![Graph showing expected profit vs. well yield](image)

Fig. 4. Expected profit (1000 $ yr$^{-1}$) as a function of available well yield (m$^3$ day$^{-1}$) and the percentile of the crop-water production function. Lower percentiles characterize production in years with drier and hotter weather conditions that are less favourable for crop growth. Conversely, higher percentiles reflect production in wetter years that are more favourable for crop growth.

3.2. Profitability of groundwater-fed irrigation

The changes in irrigation practices described in Section 3.1, in turn, affect the profitability of groundwater-fed irrigated agriculture. Fig. 4 shows that expected profit is strongly influenced by variability in weather conditions and irrigation decision making. Maximum profits for the 10th percentile of the crop-water production function are only $15,900 yr$^{-1}$ compared to $49,570 yr$^{-1}$ for the 90th percentile, a difference of 312%. Lower maximum profits in drought years are caused by two main factors. First, the maximum crop yield that is obtainable in drier, hotter years is lower than in wetter years that have less incidences of damaging extreme heat events. For example, Fig. 1 illustrates that the maximum crop yield for 10th and 90th percentile functions, given a daily irrigation constraint of 20 mm day$^{-1}$, are 11.8 and 14.0 tonne ha$^{-1}$ respectively, a difference of 18.6%. Second, and more significantly, the optimal volumetric irrigation use for a high yielding well is much higher in drier years than wetter years. Optimal expected irrigation use is equal to 402,246 m$^3$ yr$^{-1}$ for the 10th percentile production function and a maximum well yield of 10,000 m$^3$ day$^{-1}$. Contrastingly, for the same well yield, expected irrigation demand for the 90th percentile production function is equal to 294,314 m$^3$ yr$^{-1}$. Even with the relatively low cost of groundwater extraction in our model, these higher irrigation requirements contribute to a large proportion of the difference in expected field level profits between wet and dry growing seasons.

Fig. 4 also demonstrates the important role that well pumping capacity plays in buffering economic production outputs. For the 10th percentile production function, indicative of drought conditions that may become more frequent in the future as a result of climate change, the relationship between profits and well yield is almost completely linear. This reflects the losses that are incurred due to the large reductions in irrigated area that occur across


have a significant effect during the earlier stages of the growing season. This may buffer some of the negative effects of lower well yields, in particular, could be used by a regulator to reduce the volume of water use quotas or improvements in irrigation technology, for example, could be used by a regulator to reduce the volume of groundwater that is extracted for irrigation, with the aim of increasing the long-term resilience of agriculture to climate change. Our results have demonstrated that access to high-yielding groundwater-fed irrigation for a case study of corn production in the Texas High Plains region of the United States. Our results have demonstrated that access to high-yielding pumping wells plays an important role in buffering the negative biophysical and economic effects of extreme weather events such as droughts. Furthermore, we suggest that the inability of previous integrated modelling assessments (e.g., Bulatiewicz et al., 2010; Steward et al., 2013; Mulligan et al., 2014) to model explicitly the combined effects of dynamic changes in well yield and climate variability on agricultural groundwater use decisions may lead to unreliable predictions of the long-term sustainability and resilience of irrigated agriculture.

Our findings have important implications for the management of groundwater resources, in particular when viewed in the context of projected climate change. Low or declining well yields, which may be caused by either depletion of groundwater resources or naturally low yielding geological characteristics of an aquifer, are a problem faced by farmers in many major agricultural production regions around the world (Aeschbach-Hertig and Gleeson, 2012; Scanlon et al., 2012; McGuire, 2014). In many of these regions, aquifer depletion and demand for groundwater-fed irrigation are expected to increase in the years to come, simultaneous to projected increases in both the frequency and intensity of extreme drought events (Strzepek et al., 2010; Dai, 2011; Peterson et al., 2013). The results presented in this study indicate that such combined changes are likely to increase significantly the production risks faced by irrigated agriculture and may impose large negative economic costs on rural communities and the wider economy in general. Consequently, where recharge rates are sufficient to make it feasible hydrologically, groundwater policies should be designed to manage well pumping capacities in order to increase the long-term resilience of agriculture to climate change. Water use quotas or improvements in irrigation technology, for example, could be used by a regulator to reduce the volume of groundwater that is extracted for irrigation, with the aim of slowing, or even halting entirely, the non-linear reductions in well yields that will occur as aquifer saturated thickness is depleted.

### 4. Implications and concluding remarks

In this study, a set of numerical simulations have been presented that evaluate the joint effects of intraseasonal groundwater availability and weather conditions on the optimal productivity and profitability of groundwater-fed irrigation for a case study of corn production in the Texas High Plains region of the United States. Our results have demonstrated that access to high-yielding pumping wells plays an important role in buffering the negative biophysical and economic effects of extreme weather events such as droughts. Furthermore, we suggest that the inability of previous integrated modelling assessments (e.g., Bulatiewicz et al., 2010; Steward et al., 2013; Mulligan et al., 2014) to model explicitly the combined effects of dynamic changes in well yield and climate variability on agricultural groundwater use decisions may lead to unreliable predictions of the long-term sustainability and resilience of irrigated agriculture.

Our findings have important implications for the management of groundwater resources, in particular when viewed in the context of projected climate change. Low or declining well yields, which may be caused by either depletion of groundwater resources or naturally low yielding geological characteristics of an aquifer, are a problem faced by farmers in many major agricultural production regions around the world (Aeschbach-Hertig and Gleeson, 2012; Scanlon et al., 2012; McGuire, 2014). In many of these regions, aquifer depletion and demand for groundwater-fed irrigation are expected to increase in the years to come, simultaneous to projected increases in both the frequency and intensity of extreme drought events (Strzepek et al., 2010; Dai, 2011; Peterson et al., 2013). The results presented in this study indicate that such combined changes are likely to increase significantly the production risks faced by irrigated agriculture and may impose large negative economic costs on rural communities and the wider economy in general. Consequently, where recharge rates are sufficient to make it feasible hydrologically, groundwater policies should be designed to manage well pumping capacities in order to increase the long-term resilience of agriculture to climate change. Water use quotas or improvements in irrigation technology, for example, could be used by a regulator to reduce the volume of groundwater that is extracted for irrigation, with the aim of slowing, or even halting entirely, the non-linear reductions in well yields that will occur as aquifer saturated thickness is depleted.

Improvements in irrigation technology and well design may also be of particular relevance to drought risk management in other areas of the world, such as sub-Saharan Africa where well failure is often cited as a limiting factor for the use of groundwater to buffer farmers against climate variability (MacDonald et al., 2009). In turn, these types of measures could also be combined with wider improvements in drought resilience, for example through the implementation of improved soil moisture management or the use of seasonal climate forecasts (Conway, 2011; Elliott et al., 2013) to enhance farmers’ ability to manage more effectively available irrigation pumping capacity.

The analyses presented in this paper are conditioned on a number of assumptions related to farmers’ irrigation decision making that are important to highlight as areas for future research. First, it is assumed implicitly in the use of percentile crop-water production function that the farmer knows if weather conditions during the growing season will be wetter or drier than average. Actual information available to farmers, particularly in developing countries, may not be as reliable and, therefore, the negative impacts of drought may be greater in practice, for example if the farmer plants a larger area in expectation of wetter conditions that subsequently do not arrive. In addition, the economic model of producer irrigation decision making assigns no value to the non-irrigated portion of the field and also assumes that the farmer may only select one crop type (corn). In reality, farmers may be able to mitigate some of the losses observed in Fig. 4 by switching to less water intensive, drought tolerant, or dryland crop varieties as an intermediate step before removing land from agricultural production entirely. Nevertheless, it is important to note that inclusion of dryland crop choices in our model would not affect our finding that the combination of low well yields and drought conditions reduce the overall value and resilience of groundwater-fed irrigation. Indeed, if a farmer was able to generate income from dryland farming this would provide further incentive to reduce the field area devoted to irrigated production when well yield is limited and drought conditions are anticipated. Future research could seek to extend the modelling framework applied in this study to consider decisions amongst multiple crop types with varying water requirements, along with mathematical specification of farmers’ pre-season expectations about weather conditions. Furthermore, future research should also aim to link the modelling framework with a hydrological model to enable evaluation of how farmers’ irrigation decision making, groundwater levels, and well yields will co-evolve over time. In particular, it would be valuable to explore how farmers potential responses to reductions in well yields, for example drilling of additional wells or the purchasing of more powerful pumping equipment to boost yields, may help them to mitigate against increased exposure to drought risk and how, in turn, this may influence the long-term sustainability and resilience of groundwater-fed irrigation.

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