The buffer value of groundwater when well yield is limited

T. Foster^{a,b,*}, N. Brozović^b, C. Speir^c

^a*School of Mechanical, Aerospace & Civil Engineering, University of Manchester, Manchester, United Kingdom*

^b*Robert B. Daugherty Water for Food Global Institute, University of Nebraska, Lincoln, Nebraska, United States*

^c*National Oceanic and Atmospheric Association (NOAA), Southwest Fisheries Science Center, Santa Cruz, California, United States*

Abstract

A large proportion of the total value of groundwater in conjunctive use systems is associated with the ability to smooth out shortfalls in surface water supply during droughts. Previous research has argued that aquifer depletion in these regions will impact farmers negatively by reducing the available stock of groundwater to buffer production in future periods, and also by increasing the costs of groundwater extraction. However, existing studies have not considered how depletion may impact the productivity of groundwater stocks in conjunctive use systems through reductions in well yields. In this work, we develop a hydro-economic modeling framework to quantify the effects of changes in well yields on the buffer value of groundwater, and apply this model to an illustrative case study of tomato production in California's Central Valley. Our findings demonstrate that farmers with low well yields are forced to forgo significant production and profits because instantaneous groundwater supply is insufficient to buffer surface water shortfalls in drought years. Negative economic impacts of low well yields are an increasing function of surface water variability, and are also greatest for farmers operating less efficient irrigation systems. These results indicate that impacts of well yield reductions on the productivity of groundwater are an

*Corresponding author

Email address: timothy.foster@manchester.ac.uk (T. Foster)

important economic impact of aquifer depletion, and that failure to consider this feedback may lead to significant errors in estimates of the value of groundwater management in conjunctive use systems.

Keywords:

Conjunctive use, Irrigation, Groundwater depletion, Well yield, Buffer value

1. Introduction

Conjunctive use of surface water and groundwater is a common practice in many irrigated agricultural regions worldwide, such as California, India, and Spain (Foster and van Steenberg, 2011; Singh, 2014; Scanlon et al., 2016). Groundwater plays two important roles in these systems. Firstly, groundwater increases total water supply for both agriculture and other sectors. Secondly, it increases supply reliability by providing a stable buffer against uncertain surface water availability (rainfall and/or flows in rivers or canals) caused by climate variability and irrigation system management.

Extensive research has been conducted by both economists and engineers over recent decades to quantify the buffer value of groundwater (Tsur, 1990; Tsur and Graham-Tomasi, 1991; Provencher and Burt, 1994; Knapp and Olson, 1995; Tsur, 1997; Ranganathan and Palanisami, 2004; Pulido-Velázquez et al., 2006; Marques et al., 2009; Palanisami et al., 2012). Universally, this work has shown that a significant proportion of the total economic value of groundwater in a conjunctive use setting is related to the ability of groundwater stocks to buffer production against the risks posed by stochastic surface water supplies (Gemma and Tsur, 2007; Tsur, 2015). Additionally, a related body of literature has also demonstrated that groundwater stocks may also have large value as a means of adapting to sudden events or shocks that disrupt surface water supplies, such as natural disasters (Reichard et al., 2010) or droughts (de Frutos Cachorro et al., 2014).

The majority of existing research that has evaluated the stabilization or buffer value of groundwater has considered situations where only surface water

25 supply is constrained. In many regions worldwide, however, groundwater stocks
26 are declining rapidly as a result of long-term rates of abstraction that far outstrip
27 natural recharge (Aeschbach-Hertig and Gleeson, 2012; Richey et al., 2015).
28 Aquifer depletion is also likely to be exacerbated further in the future due to
29 increased demands on both groundwater and surface water from population
30 growth and climate change (Taylor et al., 2013; Elliott et al., 2014; Schewe
31 et al., 2014), coupled with growing needs to limit surface water abstractions
32 to protect critically endangered freshwater ecosystems and species (Grantham
33 et al., 2014; Grantham and Viers, 2014).

34 An important consequence of groundwater depletion is the reduction in well
35 yields, which occur as aquifer saturated thickness is reduced and wells become
36 unable to support high-capacity pumping for irrigation (Hecox et al., 2002).
37 Globally, well yield reductions are a commonly cited consequence of aquifer
38 depletion in areas of intensive irrigated agriculture (OECD, 2015). There is
39 significant anecdotal evidence that drawdown in Californias Central Valley over
40 recent decades (Famiglietti et al., 2011; Scanlon et al., 2012), which has increased
41 rapidly during the recent period of severe drought (Faunt et al., 2016), has led
42 to reductions in the yields of irrigation wells and, in some cases, even complete
43 well failure due to the aquifer water levels falling below the base of the well
44 intake screens (Howitt et al., 2014, 2015; Medellín-Azuara et al., 2015; Ritchel,
45 2015; Veshkin, 2015). Lower well yields constrain both total and instantaneous
46 groundwater pumping capacity, and, therefore, may have important implications
47 for the ability to use groundwater as a buffer against variable surface water flows
48 and for the value of groundwater resources. Previous research has demonstrated
49 that low well yields greatly reduce the resilience of groundwater-fed irrigation to
50 drought, and constrain significantly the amount of land that a farmer can irrigate
51 profitably (Foster et al., 2014, 2015a,b). However, this research has assumed
52 that groundwater is the sole water supply source, and, consequently, has not
53 considered the implications for farm profits and production risk of interactions
54 between groundwater well yields and stochastic surface water availability.

55 In this study, we add to the literature on conjunctive use irrigation systems

by exploring how changes in well yields influence farmers capacity to use ground-
water as a reliable buffer against stochastic surface water flows. We adapt an
existing hydro-economic modeling approach (Foster et al., 2014, 2015a) to es-
timate farmers’ optimal irrigation decision-making and profits as a function of
stochastic surface water supply, well yield, and climate. Through an example
application to irrigated tomato production in California, we demonstrate that
the economic productivity of groundwater stocks is a decreasing, non-linear
function of well yield. Our findings highlight that well yield reductions are an
important economic impact of aquifer depletion, which have not been considered
in previous studies of conjunctive use systems. The ability to limit effectively
future reductions in well yields therefore is an important factor that should be
accounted for when evaluating policies to manage groundwater use in conjunc-
tive use systems, in particular as surface water supplies become increasingly
constrained and uncertain due to climate change, population growth, and grow-
ing environmental demands for water.

2. Methods

In this section, we describe the modeling approach used to estimate the
joint effects of well yields and stochastic surface water supplies on farm water
use and profits. The numerical approach used in this study is adapted from
the methodology developed previously by Foster et al. (2014, 2015a), and has
two main components: (1) Simulation of crop yield and irrigation water use
for different levels of surface water and groundwater supply; (2) Estimation of
economically optimal irrigation decisions and farm profits for variable states of
a groundwater system. In the following sections, these two steps are described
in turn, followed by a discussion of an example application of the model to
irrigated tomato production in California’s Central Valley.

2.1. Simulation of crop yields and irrigation requirements

To estimate crop yields and irrigation water use for different surface water
allocations and groundwater pumping capacities, we use a biophysical crop sim-

85 ulation model called AquaCrop-OS (Foster et al., 2017). AquaCrop-OS is a free,
86 open-source version of AquaCrop, a crop water productivity model developed
87 by the Food and Agriculture Organization of the United Nations (FAO) (Ste-
88 duto et al., 2009). The model simulates on a daily time step dynamic changes
89 in crop growth and soil moisture at the field-level. Importantly, the model rep-
90 resents explicitly the effects of a range of environmental stressors, most notably
91 water and temperature, on crop growth processes, making it ideally suited for
92 assessments of crop production in water-constrained regions.

93 We run AquaCrop-OS iteratively to estimate irrigated crop yields and water
94 use (surface and groundwater) for different possible surface water and ground-
95 water supply constraints. Surface water supply is expressed in terms of the total
96 depth of water available to the farmer over the growing season, and our model
97 setup makes the assumption that farmers will use surface water preferentially
98 to groundwater until either the full surface water allocation is used or the end
99 of the growing season is reached. We justify this assumption based on the fact
100 that surface water is typically significantly cheaper than groundwater (Section
101 2.2 describes how our model accounts for different costs of surface water and
102 groundwater), and also because delaying use of surface water may result in that
103 water being diverted by other users especially in years when available resources
104 are over-allocated (further discussion of this assumption is provided in Section
105 4.2). We assume no seasonal limit on groundwater availability, reflecting the fact
106 that in many regions worldwide there currently are no binding limits imposed
107 on agricultural groundwater pumping (OECD, 2015). Instead, the groundwa-
108 ter supply constraint is expressed as a maximum daily irrigation application
109 rate. The instantaneous groundwater supply constraint is dependent on well
110 yield and irrigated area, which together limit the maximum depth of water that
111 can be applied on any day in AquaCrop-OS. This constraint is important as
112 low instantaneous application rates may be insufficient to meet peak crop water
113 requirements during sensitive growth periods, leading to the build up of soil
114 moisture deficits and reductions in crop yields in particular when surface water
115 supply is exhausted early in the growing season (Foster et al., 2014).

116 Decisions about irrigation use in AquaCrop-OS depend on the rules that
 117 are specified for intraseasonal irrigation scheduling. We assume that farmers’
 118 intraseasonal scheduling heuristics can be characterized by the selection of a
 119 soil moisture target strategy (Foster et al., 2014). The soil moisture target
 120 strategy represents the proportional soil moisture level at which irrigation is
 121 initiated during the four main crop growth stages considered by AquaCrop-OS:
 122 (1) Initial stage; (2) Crop development stage; (3) Mid-season stage; (4) Late-
 123 season stage. The soil moisture target is allowed to vary between these growth
 124 stages, reflecting the differing sensitivity of crop growth processes to water stress
 125 at different points throughout the growing season. In each stage, the lower the
 126 soil moisture target, the more the root zone soil profile is allowed to dry out
 127 between irrigation events. Choosing a lower soil moisture target therefore will
 128 enable limited surface water supplies to last longer in to a growing season.
 129 However, if large soil moisture deficits are allowed to build up then water stress
 130 may constrain crop growth processes, resulting in reductions in yield at the end
 131 of the season, or, in extreme cases, even complete crop failure.

132 Simulations are performed iteratively for each possible combination of in-
 133 traseasonal soil moisture target strategy, surface water and groundwater supply
 134 constraints. The resulting outputs are three $M \times S \times G$ matrices, describing
 135 simulated (1) crop yield; (2) surface water use; and (3) groundwater use; where
 136 M is the number of soil moisture target strategies, S is the number of surface wa-
 137 ter allocations, and G is the number of groundwater supply constraints. Note
 138 that the previous methodology developed by Foster et al. (2014, 2015a) also
 139 considers the effects on crop yields and irrigation use of interannual variability
 140 in weather variables (precipitation, temperature, and reference evapotranspira-
 141 tion), which are inputs to AquaCrop-OS simulations. However, for the purposes
 142 of this study we focus on weather conditions for an individual average year, as
 143 will be discussed in Section 2.3.

144 2.2. Economic optimization

145 We use the crop yield and irrigation data generated by AquaCrop-OS to
 146 determine farmers' private economically optimal irrigation decision-making and
 147 profits given stochastic surface water supply and available well yield. Our eco-
 148 nomic model assumes that the farmer's irrigation decision has two components:
 149 (1) an extensive margin choice of how much land to plant with irrigated crops;
 150 and (2) an intensive margin decision of the soil moisture target strategy to fol-
 151 low during the growing season. For a given surface water allocation and well
 152 yield, the optimal joint irrigation decision is determined by solving Equations
 153 1-2 below.

$$[A^*, S^*, \Pi^*] = \max_{\{A, S\}} \Pi_{A, S} \quad (1)$$

$$\begin{aligned} \Pi_{A, S} = & \left[Y(S, q_{sw}, q_{gw}) \cdot (p_c - c_h) - c_{fi} - X_{sw}(S, q_{sw}) \cdot c_{w_{sw}} \right. \\ & \left. - X_{gw}(S, q_{gw}) \cdot c_{w_{gw}} \right] \cdot A - [c_f \cdot A_{max}] \\ & + [(R_d - c_{fd}) \cdot (A_{max} - A)] \end{aligned} \quad (2)$$

Subject to:

$$A \leq A_{max}$$

$$q_{sw} = \frac{Q_{sw}}{A}$$

$$q_{gw} = \frac{Q_{gw}}{A}$$

154 Where A^* , S^* , and Π^* are the optimal irrigated area (ha), soil moisture target
 155 strategy, and maximized profits, respectively, Π is the profit (\$), Y is irrigated
 156 crop yield (tonne ha⁻¹), X is seasonal irrigation (mm), S is the soil moisture
 157 target strategy, A is irrigated area (ha), A_{max} is the total field area (ha), p_c is
 158 the crop price (\$ tonne⁻¹), c_h is the crop harvesting cost (\$ tonne⁻¹), c_f is the
 159 fixed production cost per unit area (\$ ha⁻¹), c_{fi} is the fixed production cost per

160 unit irrigated area ($\$ \text{ ha}^{-1}$), c_w is the cost of irrigation ($\$ \text{ ha-mm}^{-1}$), R_d is a
 161 fixed revenue from dryland crop production on the non-irrigated land area ($\$$
 162 ha^{-1}), c_{fd} is the fixed production cost per unit non-irrigated area ($\$ \text{ ha}^{-1}$), Q
 163 is the volumetric water supply constraint (ha-mm yr^{-1} or day^{-1}), and q is the
 164 per-area water supply constraint (mm yr^{-1} or day^{-1}). Subscripts sw and gw
 165 denote surface water and groundwater, respectively.

166 A number of important features in Equations 1 and 2 warrant further dis-
 167 cussion. First, the farmer may adjust per-area surface water and groundwater
 168 supply by changing the number of irrigated acres planted at the start of the
 169 growing season. Land that is not irrigated will still generate revenue, but at
 170 a significantly lower rate due to the reduced returns from dryland relative irri-
 171 gated crop production. Farmers with less secure surface water supplies and/or
 172 low well yields therefore must make trade-offs between maximizing potential
 173 irrigated production areas, and ensuring that adequate soil moisture levels can
 174 be maintained during the season to avoid crop yield losses or failure. Addition-
 175 ally, extensive margin decisions will be further affected by the fact that some
 176 fixed costs, c_f , are payable on the full field area irrespective of whether all avail-
 177 able land is irrigated, for example if an advanced irrigation system has been
 178 installed on the full field. Finally, the model also makes the assumption that
 179 the farmer knows with certainty when making planting decisions what level of
 180 surface water allocation they will receive. This is realistic in most conjunctive
 181 use systems, where surface water flows typically are controlled by reservoir sys-
 182 tems, and farmers are informed before the start of the growing season how much
 183 water they should receive. For example, in our study area of California, the ma-
 184 jority of farmers receive surface water through centrally-operated reservoirs and
 185 canals, such as the Central Valley Project and State Water Project. In these
 186 systems, water allocations are announced before planting based on observed
 187 snowpack and reservoir levels, and, historically, it is very rare for deliveries to
 188 be reduced once the growing season has begun (U.S. Bureau of Reclamation,
 189 2016). However, in situations where this assumption does not hold, the model
 190 could be adapted easily by specifying Q_{sw} as an expectation of the surface water

191 allocation for the upcoming season (this will explore further in Section 2.3).

192 Equation 1 is solved repeatedly by drawing values of Q_{sw} at random from a
 193 specified distribution, holding Q_{gw} fixed. We then take the mean of the maxi-
 194 mized profits across all surface water draws to obtain an expected value of profits
 195 as a function of Q_{gw} , $\mathbb{E}[\Pi(Q_{gw})]$. Using this estimate, the total value added
 196 by access to groundwater, $V(Q_{gw})$, is then calculated as the difference between
 197 $\mathbb{E}[\Pi(Q_{gw})]$, and the expectation of profits with no access to groundwater (i.e.
 198 when $Q_{gw} = 0$) (Equation 3).

$$V(Q_{gw}) = \mathbb{E}[\Pi(Q_{gw})] - \mathbb{E}[\Pi(0)] \quad (3)$$

199 We can also calculate the total loss in value from reducing well yield to a
 200 given level, $L(Q_{gw})$, by calculating the difference between $\mathbb{E}[\Pi(Q_{gw})]$, and the
 201 expectation of profits with unconstrained groundwater supply (Q_{gw}^*) (i.e. un-
 202 limited well yield, which is characteristic of assumptions in previous conjunctive
 203 use models) as shown in Equation 4.

$$L(Q_{gw}) = \mathbb{E}[\Pi(Q_{gw}^*)] - \mathbb{E}[\Pi(Q_{gw})] \quad (4)$$

204 2.3. Example application

205 We apply our model to a case study of irrigated tomato production in Cal-
 206 ifornia’s Central Valley. Tomato production is a significant component of the
 207 agricultural economy in California, with the state producing over 90 % of U.S.
 208 processing tomatoes and 35 % of total global production (Hartz et al., 2008).
 209 Tomato producers are heavily dependent on reliable water supplies for irrigation,
 210 as California’s Mediterranean style climate means that precipitation during the
 211 growing season is minimal. However, the reliability of surface water supplies is
 212 threatened by a combination of growing agricultural, urban, and environmental
 213 demands, coupled with reductions in surface runoff due to enhanced drought
 214 risk and climate change (Mehta et al., 2013; Seager et al., 2013). Many farmers,
 215 therefore, increasingly rely on groundwater as an additional source of water sup-
 216 ply (Faunt et al., 2009), which can be used to both buffer surface water deficits

217 and increase total farm water availability. However, decades of groundwater
218 abstraction in excess of natural recharge have led to widespread declines in wa-
219 ter tables across the Central Valley Aquifer (Famiglietti et al., 2011; Scanlon
220 et al., 2012), with resultant reductions in well pumping capacities threatening
221 the future viability of the aquifer as a buffer against stochastic surface water
222 deliveries.

223 We parameterize AquaCrop-OS using representative weather, soil, and crop
224 data for irrigated tomato production in California. Daily weather time series
225 (precipitation, maximum and minimum temperature, and reference evapotran-
226 spiration) required to run AquaCrop-OS are obtained from the California Ir-
227 rigation Management Information Systems (CIMIS) weather station at Davis
228 for the year 2003 (data available at: <http://www.cimis.water.ca.gov>), which
229 represents a year with approximately average growing season (May - August)
230 precipitation (25 mm) and reference evapotranspiration (800 mm). Effects of
231 inter-annual weather variability are not considered, as both precipitation (0 - 79
232 mm) and reference evapotranspiration (691 - 859 mm) show relatively limited
233 variability across the 30 year record at Davis. Soil type in AquaCrop-OS is
234 assumed to be a loamy soil, with the initial water content in the soil profile at
235 planting (May 1) uniformly equal to 70 % of total available water (i.e. water
236 storage between field capacity and permanent wilting point). This value was
237 obtained by running AquaCrop-OS continuously for a period of 30 years (1986-
238 2015) at Davis, and taking the average initial soil moisture condition across
239 all years. Finally, we assume the default values for crop parameters describing
240 tomato growth in AquaCrop-OS (Raes et al., 2016). This choice is justified by
241 previous research, which has shown that AquaCrop simulates accurately tomato
242 yield response to water in climatically and agronomically similar Mediterranean
243 environments (Rinaldi et al., 2011; Katerji et al., 2013; Linker et al., 2016).
244 Furthermore, average irrigated tomato yields simulated by AquaCrop-OS (126
245 tonnes ha⁻¹) correspond closely to recent reported yields in California (121
246 tonnes ha⁻¹) (data available at: https://www.nass.usda.gov/Quick_Stats).

247 We perform simulations using AquaCrop-OS, as described in Section 2.1, for

248 potential combinations of per-area surface water and groundwater supply, and
 249 a range of intraseasonal soil moisture target strategies. Surface water supply
 250 constraints are varied from 0 to 900 mm ha⁻¹ year⁻¹ in increments of 25 mm
 251 yr⁻¹, and groundwater supply constraints range from 0 to 20 mm ha⁻¹ day⁻¹ in
 252 increments of 0.5 mm ha⁻¹ day⁻¹. The soil moisture target in each of the four
 253 main crop growth stages is varied from 30 % to 90 % in increments of 2.5 %, and
 254 we ignore irrigation strategies outside this range as these strategies would result
 255 in either wasteful over-irrigation or high risks of crop failure. We repeat simula-
 256 tions for the two most common irrigation methods used for tomato production in
 257 California: (1) furrow irrigation; and (2) sub-surface drip irrigation. An impor-
 258 tant difference between these techniques is the efficiency with which irrigation
 259 is applied, defined here as the proportion of applied water that reaches the crop
 260 root zone. AquaCrop-OS accounts directly for two factors influencing irrigation
 261 efficiency, namely deep percolation of applied water below the root zone and
 262 evaporation of water from soil surface layers (Steduto et al., 2009). The latter
 263 is affected by the proportion of the soil surface that is wetted by irrigation (the
 264 higher the percentage, the more applied water may be lost to non-beneficial soil
 265 evaporation), which we set equal to 0 % for sub-surface drip and 60 % for furrow
 266 following guidelines given in Raes et al. (2016). AquaCrop-OS, however, does
 267 not represent directly other significant factors affecting irrigation inefficiency,
 268 such as surface runoff and evaporation of flowing water. For sub-surface drip
 269 systems, these losses will be negligible as water is applied directly to the crop
 270 root zone. However, for furrow systems, losses may be large, and, therefore,
 271 we assume that 20 % of any applied irrigation does not enter the soil profile
 272 consistent with typical losses observed in California (Bali et al., 2001; Arnold
 273 et al., 2014).

274 Solving the economic optimization (Section 2.2) requires a number of eco-
 275 nomic parameters to be defined (Table 1). Tomato crop price is defined accord-
 276 ing to average tomato prices received by producers in California over the period
 277 2011-2015 (data available at: https://www.nass.usda.gov/Quick_Stats). Har-
 278 vest and fixed costs for irrigated tomato production are taken from recent crop

279 budgets developed by University of California, Davis (Miyao et al., 2014a,b).
 280 For sub-surface drip irrigation an additional fixed cost is also estimated per unit
 281 of field area (irrespective of whether that land is irrigated or not), to account
 282 for costs of installing and maintaining the drip irrigation system. Revenue and
 283 fixed costs for dryland production on the non-irrigated portion of the field are
 284 assumed to be equal to typical values for dryland oat hay production, a com-
 285 mon rotation crop for tomato producers in California, as reported in recent
 286 crop budgets (Long et al., 2012). Surface water is assumed to be cheaper than
 287 groundwater, reflecting the fact that surface water rates in California, such as for
 288 supply from the Central Valley Project, are subsidized heavily, whereas farmers
 289 must pay the full energy cost of pumping groundwater from tens or hundreds
 290 of meters below the land surface. Finally, we assume that the maximum field
 291 area is 65 ha, and that the farmer can adjust irrigated acreage in increments of
 292 0.5 ha.

Table 1: Economic model parameters

Parameter	Cost
Crop price (\$ tonne ⁻¹)	90
Harvest cost (\$ tonne ⁻¹)	10
Dryland revenue (\$ ha ⁻¹)	926.7
Fixed cost (dryland area) (\$ ha ⁻¹)	840.2
Fixed cost (irrigated area) (\$ ha ⁻¹)	4942 (Furrow) 4386 (Drip)
Fixed cost (field) (\$ ha ⁻¹)	0 (Furrow) 519 (Drip)
Surface water cost (\$ ha-mm ⁻¹)	0.02
Groundwater cost (\$ ha-mm ⁻¹)	0.04

293 Following the methodology described in Section 2.2, we estimate the value
 294 of groundwater for tomato production as a function of well yield for three al-
 295 ternative surface water distributions and the two irrigation methods (furrow
 296 and sub-surface drip) described above. Surface water deliveries are expressed
 297 as percentages of full deliveries, defined as the amount of surface water needed

to meet full crop water requirements on the maximum field area (58,500 ha-mm
 yr⁻¹). All three surface water distributions are uniform, with an upper bound of
 100 % delivery. However, the lower bound differs between each distribution to
 reflect varying levels of surface water supply variability (Table 2). For each irri-
 gation method (i.e. furrow or sub-surface drip), the economic model of farmer
 irrigation decision-making is solved for 1000 random draws from each specific
 surface water distribution. Comparison of optimization outputs provides valu-
 able insights about how the value of groundwater is affected by interactions
 between well yields, irrigation system efficiency, and the level of variability in
 surface water deliveries faced by the farmer.

Table 2: Properties of surface water distributions. Names of each distribution in the first
 column (low, moderate, and high) reflect the degree of surface water variability

Distribution	Lower bound (%)	Upper bound (%)	Mean (%)
Low	80	100	90
Moderate	40	100	70
High	0	100	50

Implicit to the analyses described above is the assumption that the farmer
 knows with certainty what surface water allocation they will receive at the time
 planting decisions are made in each year. As discussed in Section 2.2, this is a
 reasonable assumption in most of California where a large proportion of farmers
 receive water through engineered, centrally-controlled systems of reservoirs and
 canals. Nonetheless, water managers in the region, and indeed in other similar
 conjunctive use systems worldwide, do have the authority to reduce surface
 water deliveries once the growing season has begun, in particular to farmers
 with junior surface water rights in over-allocated basins. It is therefore an
 interesting exercise to explore to what extent uncertainty about surface water
 deliveries at the time of planting affects the impacts of low well yields on crop
 production risk and profits in conjunctive use systems. In order to answer
 this question, we repeat the analyses described above, but now assuming that

irrigation decisions are made on the basis of an expected surface water delivery (i.e. $Q_{sw} = E(Q_{sw})$ in Equation 2, where the expectation is equal to the mean surface water delivery for a given distribution). Actual profits subsequently are calculated by re-solving Equation 2, given these irrigation decisions and actual surface water deliveries. Profits under uncertain surface water supply finally are compared with those obtained when surface water deliveries are known with certainty each year, providing an indication of the additional costs associated with reduced well yields when the farmer has limited knowledge of how much surface water supply to expect at the time planting decisions are made.

3. Results

3.1. Well yield impacts on groundwater value

We begin by analysing the effects of well yield on the value of groundwater for furrow irrigated tomato production under the moderate variability surface water distribution detailed in Table 2.

Figure 1 shows changes in the optimal irrigated area and crop yield as a function of well yield, and demonstrates that the relationship between tomato production and well yields is non-monotonic. When the farmer has no access to groundwater (i.e. when well yield is set equal to zero), the mean optimal irrigated area and crop yield are equal to 48.5 ha and 91.8 tonne ha⁻¹, respectively, with the remainder of the field area cultivated with dryland oat hay. There is also large interannual variability in tomato production, caused by the stochastic fluctuations in surface water deliveries. Increasing well yield raises gradually the mean level of tomato production (both in terms of area irrigated and per-area crop yields), and reduces variability in irrigated crop production from year to year. However, a large well yield (5350 m³ day⁻¹ or greater, 980 gpm and above) is required for groundwater supply to buffer production fully against surface water variability. This result reflects the fact that tomatoes are sensitive to water deficits during the growing season, which occur when surface

349 water supply is limited and well yield is insufficient to satisfy peak crop water
 350 demands.

Figure 1: Optimal tomato irrigated area (left) and yields (right) as a function of well yield ($\text{m}^3 \text{ day}^{-1}$) and stochastic surface water supply. In each plot, the solid black line shows the mean response and the grey shaded area represents the bounds of the 10-90th percentiles from the 1000 random draws. Tomatoes are assumed to be furrow irrigated, and surface water deliveries are drawn from the moderate distribution given in Table 2. Note that $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm.

351 The effects of well yield on farmers' irrigation decisions and tomato produc-
 352 tion output are reflected in the optimal farm profits predicted by our model.
 353 Figure 2a shows that profits exhibit a similar non-linear response to well yield,
 354 with expected profits peaking at around \$325,750 for well yields above 5500 m^3
 355 day^{-1} (1000 gpm) when the full field area is cultivated with high-value irrigated
 356 tomatoes in all years, relative to a value of around \$242,730 when no groundwa-
 357 ter supply is available and significant portions of the field have to be turned over
 358 to lower value dryland production in years of lower surface water availability.
 359 The potential loss in economic value from reductions in well yields is visualized
 360 in Figure 2b. Importantly, Figure 2b demonstrates that below well yields (and
 361 by implication aquifer saturated thickness) of around $5500 \text{ m}^3 \text{ day}^{-1}$ (1000 gpm)
 362 the productivity of groundwater decreases significantly due to an inability for
 363 stocks to buffer production effectively against stochastic fluctuations in surface

364 water deliveries. This result has important implications for groundwater man-
 365 agement in conjunctive use systems worldwide, and, in particular, suggests that
 366 policies to maintaining well yields will be important to ensure future drought
 367 resilience. Further discussion on this topic and the implications of our findings
 368 for groundwater management is provided in Section 4.1.

Figure 2: (Left): Response of farm profits (\$) to well yield ($\text{m}^3 \text{ day}^{-1}$). The solid black line shows the mean response and the grey shaded area represents the bounds of the 10-90th percentiles from the 1000 random draws. (Right): Cumulative loss of profits (\$) from reductions in well yields relative to when groundwater supply is unconstrained. Data in both plots are for furrow irrigated tomatoes, and for surface water deliveries drawn from the moderate distribution given in Table 2. Note that $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm.

369 3.2. Sensitivity to surface water distribution

370 The results presented thus far have only considered one possible distribution
 371 of surface water deliveries. It is important, therefore, to assess how the value
 372 of groundwater, and in particular the sensitivity to changes in well yields, may
 373 differ under conditions of higher or lower variability in surface water deliveries.

374 Figure 3 shows the mean optimal irrigated area and tomato crop yield pre-
 375 dicted by our model as a function of well yield for the three surface water
 376 distributions described in Table 2, assuming that tomatoes are irrigated using
 377 a furrow irrigation system. Figure 3 demonstrates clearly that the sensitivity of

378 tomato production to well yields is dependent on the frequency and magnitude
 379 of surface water supply deficits. When surface water supply has a high mean and
 380 low variability (Low distribution in Table 2) the farmer is able to irrigate close
 381 to the full field area (61.5 ha out a maximum of 65 ha) with no groundwater
 382 supply, and can fully buffer production for well yields of around $3000 \text{ m}^3 \text{ day}^{-1}$
 383 (550 gpm) and above. Contrastingly, when surface water supply has a lower
 384 mean and larger variability (High distribution in Table 2), it is only optimal to
 385 irrigate 34 ha of land on average (52 % of the field area) without groundwa-
 386 ter access. The remaining land area is cultivated with lower value dryland oat
 387 hay, with significant impacts on profitability as will be discussed below. Fur-
 388 thermore, a well yield of $5750 \text{ m}^3 \text{ day}^{-1}$ or above (1050 gpm) is needed before
 389 maximum production levels on both the intensive and extensive margins can be
 390 achieved in all years.

Figure 3: Optimal tomato irrigated area (left) and yields (right) as a function of well yield ($\text{m}^3 \text{ day}^{-1}$) and three different surface water supply distributions given in Table 2. In each plot, the solid line represents the mean response and the shaded area represents the bounds of the 10-90th percentiles from 1000 random draws. Data in all plots are for furrow irrigated tomatoes. Note that $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm .

391 Figure 4 demonstrates how the differences in irrigation decisions and tomato
 392 production outputs shown in Figure 3 translate in to economic losses as well

393 yields are reduced. In all cases, below a given well yield, further reductions in
 394 well yields have negative economic impacts for farmers, as they are forced to for-
 395 goe higher value irrigated tomato production in years when surface water supply
 396 is limited. However, the timing and magnitude of economic impacts varies sub-
 397 stantially between the three surface water distributions that we have considered
 398 in our analyses. For example, reducing well yields to $3000 \text{ m}^3 \text{ day}^{-1}$ (550 gpm)
 399 leads to losses in production value of \$2,440, \$42,945, and \$83,065 for the low,
 400 moderate, and high variability distributions in Table 2, respectively. Reducing
 401 well yield further to $1500 \text{ m}^3 \text{ day}^{-1}$ (275 gpm) enhances these differences, with
 402 losses equal to \$14,725, \$72,480, and \$131,950 for the same three surface water
 403 distributions. This result highlights that reductions in well yields caused by
 404 aquifer depletion will not impact all farmers equally, with producers with the
 405 least secure water rights, or those in areas where well yields are more sensitive
 406 to depletion due to heterogeneity in aquifer properties, being most vulnerable
 407 to the loss of the intrinsic buffering capacity of groundwater stocks for irrigated
 408 crop production.

Figure 4: Cumulative loss of profits (\$) from reductions in well yields relative to when ground-
 water supply is fully unconstrained. Results are shown for the three different surface water
 supply distributions given in Table 2. All data are for furrow irrigated tomatoes. Note that
 $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm.

409 3.3. *Benefits of sub-surface drip irrigation*

410 Farmers faced with increasing and uncertain surface water supply constraints
411 can adapt in a number of ways to minimize risks to crop production when use of
412 groundwater is limited by low well yields. Adaptation options, for example, in-
413 clude drilling deeper wells to improve well yields, purchasing additional surface
414 water supply from other users through water markets, or adopting more efficient
415 irrigation systems. In this section, we assess the implications of the latter type
416 of adaptation, specifically focusing on potential benefits of switching from fur-
417 row to sub-surface drip irrigation. As described in Section 2.3, furrow irrigation
418 typically is an inefficient means of applying water as a significant proportion
419 of irrigation often is lost to non-beneficial surface runoff, deep percolation, and
420 evaporation. In contrast, sub-surface drip irrigation is a highly efficient method
421 of applying water directly to the root zone of the crop, and, therefore, is in-
422 creasingly being adopted by tomato producers in water constrained areas of
423 California. For example, Tindula et al. (2013) show that 63% of processing
424 tomatoes grown in California are now irrigated using drip technologies (85% of
425 which is sub-surface) supplied by surface water deliveries, and, in times of water
426 shortage, groundwater pumping

427 Figure 5 shows how optimal irrigated area and tomato crop yields differ
428 for combinations of surface water distribution (Table 2) and irrigation method
429 (furrow or drip). An important insight from Figure 5 is that both irrigated area
430 and tomato yields under sub-surface drip irrigation are always equal to or higher
431 than under furrow irrigation. Differences between results for furrow and sub-
432 surface drip irrigation are most pronounced for the surface water distributions
433 with lower means and higher variability (Moderate and High distributions in
434 Table 2, Panels b and c in Figure 5), and for lower well yields. This reflects
435 the fact that adoption of sub-surface drip irrigation has two main benefits:
436 (1) it reduces total seasonal irrigation requirements, enabling irrigated tomato
437 production areas to be sustained for lower surface water deliveries irrespective
438 of whether a back-up groundwater supply is available; and (2) it minimizes non-
439 beneficial losses, ensuring that limited instantaneous groundwater supplies can

440 be utilized effectively to satisfy peak water requirements of high-value irrigated
 441 crops and thereby avoiding the build-up of damaging soil moisture deficits during
 442 the growing season.

Figure 5: Optimal tomato irrigated area (left) and yields (right) as a function of well yields ($\text{m}^3 \text{ day}^{-1}$) and two different irrigation methods (furrow and sub-surface drip). Each column relates to results for one of the three surface water supply distributions given in Table 2: (a) Low variability distribution; (b) Moderate variability distribution; (c) High variability distribution. In each plot, the solid line represents the mean response and the shaded area represents the bounds of the 10-90th percentiles from 1000 random draws. Note that $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm.

443 Figure 6 demonstrates the economic impacts of reducing well yields for each
 444 combination of surface water distribution and irrigation method. In particular,
 445 Figure 6 illustrates two important findings about the interactions between well
 446 yield, surface water variability, and irrigation efficiency that emerge from our

447 analyses. First, tomato producers with more reliable surface water rights (Figure
 448 6a) may be able to eliminate dependence on groundwater entirely by switching to
 449 sub-surface drip irrigation. However, groundwater may still have value for these
 450 farmers if they have access to additional land with which to expand production
 451 (we assume a land constraint of 65 ha in our analyses). Second, when surface
 452 water supply is more variable (Figures 6b and 6c), switching to sub-surface
 453 drip will have significant economic benefits, but will not be able to fully offset
 454 the losses caused by reductions in well yields and resultant declines in irrigated
 455 areas. Indeed, reducing well yields to $1500 \text{ m}^3 \text{ day}^{-1}$ (275 gpm) will still lead to
 456 economic losses of \$12,255 (4%) and \$78,470 (20%) for the moderate and high
 457 variability surface water distributions, respectively, in Table 2.

Figure 6: Cumulative loss of profits (\$) from reductions in well yields (relative to when groundwater supply is fully unconstrained) for furrow and sub-surface drip irrigated tomatoes. Each column relates to results for one of the three surface water supply distributions given in Table 2: (a) Low variability distribution; (b) Moderate variability distribution; (c) High variability distribution. Note that $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm.

458 Finally, it is worth noting that adoption of sub-surface drip may not have
 459 solely positive impacts, and could also have the unintended consequence of in-
 460 creasing long-term aquifer depletion and, as a result, exacerbating reductions
 461 in well yields and loss of irrigated production resilience. Our analysis assumes
 462 that the farmer has a land constraint of 160 acres. However, in practice, farmers
 463 may be able to use the water savings from switching to more efficient irrigation

technologies, such as sub-surface drip, to expand irrigated production areas. Previous research has demonstrated that, where this effect occurs, total consumptive water use may increase even though irrigation is used more efficiently on a per-area basis, due to the fact that much of the water “wasted” by inefficient irrigation methods is returned back to groundwater and rivers (Ward and Pulido-Velazquez, 2008; Pfeiffer and Lin, 2014). As a result, aquifer depletion may be accelerated, further reducing well yields and exacerbating long-term vulnerability to surface water supply variability.

3.4. *Effects of surface water supply uncertainty*

As discussed previously, the analysis and results reported so far have focused on conditions where the farmer knows with certainty each year what surface water allocation they will receive, although the size of that allocation varies inter-annually. However, in some circumstances, for example when water rights are insecure or in heavily over-allocated basins, the farmer may have to decide what land area to plant with irrigated and dryland crops with limited information about how much surface water supply they will receive. This has the potential to create additional volatility in production and profits for farmers with low well yields, who may be unable to buffer planted areas fully in years where surface water allocations are unexpectedly reduced. Figure 7 demonstrates this effect, showing additional reductions in profits as a function of well yield when the farmer only has knowledge of the expected surface water delivery at planting, versus when surface water deliveries are known with certainty in all years. Results in Figure 7 are shown for the three surface water distributions (low, moderate, and high variability Table 2) and two irrigation methods (furrow and sub-surface drip) considered in the previous analyses.

Consistent with the findings presented in previous sections, Figure 7 shows that uncertainty about surface water allocations has different impacts depending on interactions between the degree of variability in surface water supply, the level of on-farm irrigation efficiency, and available groundwater well yield. Producers operating high-efficiency drip irrigation systems with low variability

Figure 7: Additional loss of profits (\$) as a function of well yield when surface water supply is uncertain at the time of planting, relative to when surface water allocations are known with certainty in each year. Results are shown for furrow and sub-surface drip irrigation systems. Each column relates to results for one of the three surface water supply distributions given in Table 2: (a) Low variability distribution; (b) Moderate variability distribution; (c) High variability distribution. Note that $1 \text{ m}^3 \text{ day}^{-1}$ is equivalent to 0.183 gpm.

in surface water deliveries do not rely on groundwater in any year, and, therefore, are unaffected by uncertainty about surface water allocations. Similarly, producers with high well yields are also minimally impacted by this uncertainty, as sufficient groundwater capacity is available to buffer production against unforeseen shortfalls in surface water deliveries.

In contrast, producers with low well yields and more variable surface water supplies (panels b and c in Figure 7) suffer much larger economic losses due to uncertainty about surface water deliveries at planting. For these farmers, restricted well yields limit ability to meet crop water needs in years when surface water supply is lower than expected, leading to reductions in crop yields and, in some cases, even complete crop failure. Indeed, the large reductions in profitability found for producers with low well yields and highly variable surface water supplies (Figure 7c) are driven, in large part, by the fact that the farmer incurs significant losses in years when the irrigated tomato crop fails before harvest due to insufficient water supply. Impacts are most pronounced for those farmers operating inefficient furrow irrigation systems, because, as dis-

510 cussed previously, irrigation requirements are greater in these systems due to
511 non-beneficial losses from surface runoff, soil evaporation, and deep percolation.

512 It is important to highlight that, implicit to this analysis, is the assumption
513 that the farmer does not abandon part of the planted irrigated crop area once
514 it becomes known that surface water supply will be limited. In reality, this may
515 be an optimal adaptation, in particular for farmers with low well yields and
516 highly variable surface water supplies, and could reduce economic losses below
517 the levels predicted in this analysis. Further discussion of the implications of
518 this assumption for our findings, and suggestions for how this simplification
519 could be addressed in future model development is provided in Section 4.2.

520 4. Discussion

521 4.1. *Implications for groundwater management in conjunctive use systems*

522 The results of this study demonstrate that farmers' ability to use ground-
523 water as a reliable and effective buffer against stochastic surface water supply
524 is dependent, in large part, on reliable access to productive boreholes. Aquifer
525 depletion is a critical challenge in many conjunctive use systems, including Cali-
526 fornia's Central Valley, and is being exacerbated by more frequent droughts and
527 growing inter-sectoral competition for water. Our findings indicate that the
528 reductions in well yields caused by depletion are likely to increase significantly
529 agricultural production risk in these systems, and decrease resilience to future
530 climate variability and change if ongoing drawdown of groundwater storage is
531 not addressed.

532 Our findings contribute valuable knowledge to inform research and policy on
533 groundwater management in conjunctive use systems. Previous efforts to model
534 improved or optimal water resource management in conjunctive use systems (e.g.
535 Noel and Howitt (1982); Provencher and Burt (1993); Pulido-Velazquez et al.
536 (2004); Pulido-Velázquez et al. (2006); Schoups et al. (2006); Harou and Lund
537 (2008); Marques et al. (2009); Davidsen et al. (2016)) have assumed that aquifer
538 depletion will impact economic returns in future periods in two main ways: (1)

539 by reducing the stock of groundwater available to buffer production; and (2) by
540 increasing the costs of extracting each additional unit of groundwater. However,
541 existing research and models have not considered the impacts of depletion on
542 the productivity of groundwater stocks in future periods. In this paper, we
543 demonstrate that the biophysical and economic productivity of groundwater is
544 a decreasing, non-linear function of well yield (and, by implication, therefore of
545 saturated thickness). Our analysis is static and, we do not evaluate explicitly
546 the effects of well yield on dynamically optimal groundwater extraction and
547 management. Nevertheless, our results suggest that impacts of depletion on
548 the future productivity of groundwater via reductions in well yield may be an
549 important factor affecting the value of groundwater management decisions.

550 The effect of well yield on the productivity and buffer value of groundwater
551 also has important implications for the potential distributional effects of ground-
552 water management policies. As an aquifer is depleted, physical reductions in
553 well yields and their impacts on economic returns will not be uniform across
554 farmers. For example, producers with less secure water rights, limited ability to
555 access replacement water sources (e.g. drilling a deeper well), inflexible or water
556 intensive cropping patterns, or those located in less hydrologically productive
557 parts of an aquifer may be disproportionately impacted by aquifer depletion.
558 Previous studies have shown that heterogeneity amongst farmers in terms of
559 other factors, such as farm size, technology, or land productivity, will lead to
560 winners and losers from groundwater management (Athanasoglou et al., 2012;
561 Saak and Peterson, 2012; Guilfoos et al., 2016). To date, however, no study
562 has considered well yield and its effects on groundwater productivity to be an
563 important source of heterogeneity. A valuable area for future work would be
564 to evaluate the welfare effects of policies that target water use reductions in
565 space and time to minimize negative impacts of well yield reductions. Water
566 markets, for example, have been suggested as solutions to reduce streamflow de-
567 pletion impacts from groundwater pumping (Thompson et al., 2009; Palazzo
568 and Brozović, 2014; Wheeler et al., 2016), and, in principle, could also be used
569 to encourage conservation of the productivity and buffer value of groundwater

570 in conjunctive use systems.

571 Finally, our results demonstrate some of the limitations of current methods
572 used to define and characterize the buffer value of groundwater. Existing eco-
573 nomic theory (Tsur and Graham-Tomasi, 1991; Gemma and Tsur, 2007; Tsur,
574 2015) distinguishes between the stabilization and augmentation value generated
575 by access to groundwater in conjunctive use systems. This distinction is made
576 possible because such studies assume that groundwater supply is unconstrained,
577 and that the intraseasonal distribution of water availability has limited effects
578 on revenues. This assumption is only valid, however, for large well yields that
579 do not impose meaningful constraints on intraseasonal irrigation scheduling. As
580 well yields are reduced, our findings show that the seasonal model of ground-
581 water’s buffer value breaks down for two important reasons. First, when well
582 yields are highly constrained, groundwater pumping may be insufficient to sta-
583 bilize fully water supply at the mean even if pumps are run 24/7. Second,
584 identical amounts of seasonal irrigation may produce different crop yields and
585 profits when there are intraseasonal constraints on groundwater-fed irrigation.
586 Intraseasonal restrictions on how farmers with low well yields are able to apply
587 groundwater fundamentally alter the crop-water production function (Foster
588 et al., 2014), such that, for example, applying 600 mm of surface water with
589 no constraints will produce a higher crop yield than applying 300 mm each of
590 surface water and groundwater, the latter with significant restrictions on how
591 and when irrigation can be applied. Our model demonstrates that groundwater
592 and surface water may not be perfect substitutes in a depleting aquifer setting
593 due to the constraints imposed by low well yields, and highlights the need to
594 consider the temporal distribution of water use within a season when estimating
595 the value of groundwater as a buffer against surface water variability.

596 *4.2. Model assumptions and simplifications*

597 Having discussed the key contributions and policy implications of our anal-
598 yses, it is important to discuss some assumptions made in our modeling frame-
599 work and highlight potential avenues for future research and model development.

600 First, in this study we analyze the effects of declining well yields for only one
 601 irrigated crop (tomatoes), and we assume that any non-irrigated land generates
 602 a fixed per-acre return consistent with typical returns reported for dryland oat
 603 hay production in the region. In reality, farmers in California, and indeed other
 604 conjunctive use systems, grow a diverse range of crop types. The exact economic
 605 impacts of declining well yields therefore will vary depending on the sensitivity
 606 of both the irrigated crop choice to changes in instantaneous groundwater sup-
 607 ply constraints, and the relative value of alternative production choices made
 608 on the portion of the land that is not irrigated. We have repeated our analyses
 609 for two other annual crop types, corn and cotton (results are not reported in this
 610 paper due to space limitations), that are grown in California’s Central Valley.
 611 We find that, while well yield is always a significant determinant of the value of
 612 groundwater, the threshold capacity needed to achieve full production is lower
 613 due to the greater drought tolerance of these crops (in particular cotton) rel-
 614 ative to tomatoes. Other crops, however, may have even greater sensitivity to
 615 reduced well yields than tomatoes. Perennial tree crops, for example, are widely
 616 cultivated in California, and may be more vulnerable to water supply deficits
 617 as high levels of water stress can degrade crop yield potential, and therefore
 618 revenues, for all future years in the crop’s life cycle. Planted areas of perennial
 619 crops also can’t be adjusted easily in the same way as for annual crops, due
 620 to the large investment costs at planting and because limited harvestable yield
 621 typically is produced in an initial multi-year period of development. An inter-
 622 esting extension of our analysis would be to quantify the value of maintaining
 623 well yields for perennial crop production, and, in particular, to assess how this
 624 value varies over the multi-year life cycle of a crop under conditions of stochastic
 625 surface water supply. A related analysis is performed by (Feinerman and Tsur,
 626 2014). However, their research focuses on recycled water as a back-up source of
 627 supply and, therefore, does not address the implications of aquifer depletion for
 628 drought risk in high-value perennial crop production.

629 In our analysis, we make the implicit assumption that the only back-up
 630 source of water supply is groundwater. In practice, in years when surface wa-

631 ter deliveries are reduced, the presence of informal or formal water markets
632 may provide farmers with a means of acquiring additional surface water above
633 their allocation, albeit typically at higher cost than groundwater (Howitt et al.,
634 2015). For producers of lower value crops, such as corn or cotton, it would be
635 unlikely to be cost effective to purchase additional surface water supply in order
636 to support low value production areas. However, producers of lower value crops,
637 in particular those with higher well yields, could benefit financially from sell-
638 ing their available surface water allocation to producers of higher value crops,
639 such as tomatoes and perennial tree crops, for whom the additional costs of
640 buying scarce water through a market are justified by the benefits obtained
641 from maintaining high-value irrigated production areas and avoiding risks of
642 crop failure. A water market therefore could play an important role in mini-
643 mizing the total economic costs of low well yields in years where surface water
644 allocations are constrained (e.g. during drought events). However, it is also
645 important to note that, in this situation, producers of lower value crops may
646 increase their groundwater consumption, with potential implications for future
647 well yields and resilience to surface water supply shortfalls. Alternatively, in
648 very thick aquifers such as the Central Valley, farmers' may also choose to drill
649 deeper wells to increase well yields and maintain high levels of production. For
650 example, during the recent drought in California, there has been a large spike
651 in irrigation well drilling in response to falling water tables and declining well
652 yields. Costs of well drilling are high (often several hundred thousand dollars),
653 however, and therefore may only be a financially viable adaptation for farmers'
654 growing higher value crops. Furthermore, the costs of well drilling are also an
655 additional economic impact of aquifer depletion that typically is not considered
656 in economic analysis of groundwater management. An interesting area for fu-
657 ture research therefore would be to explore to what extent welfare gains from
658 groundwater management are enhanced when considering avoided future well
659 drilling costs due to aquifer depletion.

660 An additional simplification of our analyses is that we assume, for any indi-
661 vidual daily irrigation event, that surface water and groundwater sources can't

662 be mixed. Consequently, we do not consider the possibility that farmers' could
 663 combine available surface water and groundwater supplies to maximise instan-
 664 taneous irrigation rates across the entire growing season. It is possible that
 665 blending the two water sources may be an economically optimal strategy for
 666 some farmers' with low well yields, and could limit some of the reductions in
 667 crop production and profits caused by instantaneous groundwater pumping con-
 668 straints. However, in reality, farmers must balance these potential benefits from
 669 reduced production risk with the higher energy costs associated with pumping
 670 groundwater often from significant depths. Furthermore, such a blending ap-
 671 proach may also carry risks depending on the structure and operation of surface
 672 water rights and allocations. For example, a farmer may be unable to use part
 673 of their allocation later in the growing season if pumping is curtailed prema-
 674 turely, or if the system is over-allocated and available storage is diverted by
 675 others users earlier in the season. Future work should seek to expand the model
 676 developed in this paper to assess the potential benefits of mixing of surface and
 677 groundwater sources for farmers with low well yields, considering differences in
 678 costs of surface versus groundwater resources and potential uncertainty about
 679 the window of time that it will be physically or institutionally possible to divert
 680 surface water for irrigation. Analysis could also consider instantaneous limits
 681 to surface water abstractions, for example due to limited flow in canals, which
 682 have been neglected in this study, but could interact with constraints imposed
 683 by low well yields to exacerbate crop production risks.

684 Finally, a further important area for future work will be to explore in greater
 685 detail how uncertainty about surface water deliveries at planting, in particular
 686 for farmers with less secure surface water rights, affects the costs associated with
 687 declining well yields. Our analysis has shown that producers who have limited
 688 knowledge about surface water deliveries each year suffer much greater losses of
 689 production and profits than those farmers who know with certainty how much
 690 surface water they will receive. This observation is comparable to the findings
 691 presented by García-Vila and Fereres (2012), who showed that the communi-
 692 cation date of water restrictions in a surface water irrigation system in Spain

693 has large impacts on farmers planting decisions and resultant profits. Neverthe-
 694 less, it is important to highlight that the two cases we examine represent the
 695 extreme bounds on farmers potential knowledge about surface water deliveries.
 696 In reality, actual information available to farmers will likely fall between these
 697 extremes, and some degree of pre-season adaptation through adjustments to ir-
 698 rigated areas or crop choices will be possible. Furthermore, we do not consider
 699 the potential for farmers to abandon planted land area part way through the
 700 season when surface water deliveries are uncertain. In practice, this may be
 701 an optimal adaptation for some farmers, in particular in years where deliveries
 702 are unexpectedly low and there is a need to prioritize limited water supply to
 703 avoid risks of total crop failure. Future work should seek to extend our analysis
 704 to consider under what conditions partial abandonment of crops is an optimal
 705 decision for farmers with low well yields, and to what extent such practices
 706 have occurred during recent periods of extreme water shortages in California
 707 and other conjunctive use systems.

708 5. Conclusions

709 In this paper, we advance understanding of the economic value of ground-
 710 water in conjunctive use systems by quantifying the impacts of low well yields
 711 on the productivity of groundwater as a buffer against stochastic surface wa-
 712 ter supply. Through a case study of tomato production in California’s Central
 713 Valley, we show that groundwater should not be considered an unconstrained
 714 substitute for surface water when aquifer depletion has led to reductions in well
 715 yields. Specifically, we find that farmers’ with limited well yields face increased
 716 production risk and profit volatility because instantaneous groundwater appli-
 717 cation rates are insufficient to satisfy crop water demands during drought years
 718 when surface water allocations are low, forcing farmers’ to reduce irrigated area
 719 and forgo potential production in these years. Previous research has assumed
 720 that externalities from groundwater pumping relate to reductions in the avail-
 721 ability and increases in the costs of groundwater in future periods. However, our

findings highlight the importance of also considering the impacts of depletion on the future economic productivity of groundwater stocks.

Our findings have important implications for groundwater management in conjunctive use systems worldwide. Climate change, coupled with growing intersectoral competition for water, is expected to exacerbate variability in surface water supply for irrigation in future years, and, most importantly, lead to an increase in the frequency and intensity of surface water supply restrictions. These changes are likely to result in greater reliance on groundwater resources, which, in many conjunctive use systems, already are being chronically depleted. We suggest that limiting future reductions in well yields will be important in order to maintain capacity for groundwater stocks to buffer effectively crop production against increasing variability in surface water flows. It is beyond the scope of this study to analyze which types of policies will be most effective at achieving this goal, or if such policies would be economically or institutionally practical. Future work could explore this question, and, in particular, evaluate the potential benefits of policies to target reductions in groundwater pumping spatially and temporally in ways that minimize future externalities on irrigated agriculture from declining well yields and diminished productivity of groundwater resources.

Acknowledgments

This research was funded in part by a NOAA/ECS Federal grant award entitled ‘Groundwater management in a conjunctive use system with managed flows for protected fish species’ and by USDA NIFA Award number 2012-67003-23227

References

Aeschbach-Hertig, W., Gleeson, T., 2012. Regional strategies for the accelerating global problem of groundwater depletion. *Nature Geoscience* 5, 853–861. doi:10.1038/ngeo1617.

750 Arnold, B.J., Upadhyaya, S.K., Roach, J., Kanannavar, P.S., Putnam, D.H.,
751 2014. Water advance model and sensor system can reduce tail runoff in irri-
752 gated alfalfa fields. *California Agriculture* 68, 82–88.

753 Athanassoglou, S., Sheriff, G., Siegfried, T., Huh, W.T., 2012. Optimal mech-
754 anisms for heterogeneous multi-cell aquifers. *Environmental and Resource*
755 *Economics* 52, 265–291. doi:10.1007/s10640-011-9528-0.

756 Bali, K.M., Grismer, M.E., Tod, I.C., 2001. Reduced-runoff irrigation of alfalfa
757 in Imperial Valley, California. *Journal of Irrigation and Drainage Engineering*
758 127, 123–130. doi:10.1061/(ASCE)0733-9437(2001)127:3(123).

759 Davidsen, C., Liu, S., Mo, X., Rosbjerg, D., Bauer-Gottwein, P., 2016. The cost
760 of ending groundwater overdraft on the North China Plain. *Hydrology and*
761 *Earth System Sciences* 20, 771–785. doi:10.5194/hess-20-771-2016.

762 Elliott, J., Deryng, D., Müller, C., Frieler, K., Konzmann, M., Gerten, D.,
763 Glotter, M., Flörke, M., Wada, Y., Best, N., et al., 2014. Constraints and
764 potentials of future irrigation water availability on agricultural production
765 under climate change. *Proceedings of the National Academy of Sciences* 111,
766 3239–3244. doi:10.1073/pnas.1222474110.

767 Famiglietti, J.S., Lo, M., Ho, S.L., Bethune, J., Anderson, K.J., Syed, T.H.,
768 Swenson, S.C., De Linage, C.R., Rodell, M., 2011. Satellites measure recent
769 rates of groundwater depletion in California’s Central Valley. *Geophysical*
770 *Research Letters* 38, L03403. doi:10.1029/2010GL046442.

771 Faunt, C.C., Hanson, R.T., Belitz, K., 2009. Groundwater availability of the
772 Central Valley Aquifer. Professional Paper 1766. United States Geological
773 Survey, Reston, VA, USA.

774 Faunt, C.C., Sneed, M., Traum, J., Brandt, J.T., 2016. Water availability and
775 land subsidence in the Central Valley, California, USA. *Hydrogeology Journal*
776 24, 675–684. doi:10.1007/s10040-015-1339-x.

777 Feinerman, E., Tsur, Y., 2014. Perennial crops under stochastic water supply.
778 *Agricultural Economics* 45, 757–766. doi:10.1111/agec.12120.

779 Foster, S., van Steenberg, F., 2011. Conjunctive groundwater use: a 'lost
780 opportunity' for water management in the developing world? *Hydrogeology*
781 *Journal* 19, 959–962. doi:10.1007/s10040-011-0734-1.

782 Foster, T., Brozović, N., Butler, A., Neale, C., Raes, D., Steduto, P., Fereres, E.,
783 Hsiao, T., 2017. AquaCrop-OS: An open source version of FAO's crop water
784 productivity model. *Agricultural Water Management* 181, 18–22. doi:10.
785 1016/j.agwat.2016.11.015.

786 Foster, T., Brozović, N., Butler, A.P., 2014. Modeling irrigation behavior in
787 groundwater systems. *Water Resources Research* 50, 6370–6389. doi:10.
788 1002/2014WR015620.

789 Foster, T., Brozović, N., Butler, A.P., 2015a. Analysis of the impacts of well
790 yield and groundwater depth on irrigated agriculture. *Journal of Hydrology*
791 523, 86–96. doi:10.1016/j.jhydro1.2015.01.032.

792 Foster, T., Brozović, N., Butler, A.P., 2015b. Why well yield matters for man-
793 aging agricultural drought risk. *Weather and Climate Extremes* 10, 11–19.
794 doi:10.1016/j.wace.2015.07.003.

795 de Frutos Cachorro, J., Erdlenbruch, K., Tidball, M., 2014. Optimal adaptation
796 strategies to face shocks on groundwater resources. *Journal of Economic*
797 *Dynamics and Control* 40, 134–153. doi:10.1016/j.jedc.2014.01.005.

798 García-Vila, M., Fereres, E., 2012. Combining the simulation crop model
799 aquacrop with an economic model for the optimization of irrigation man-
800 agement at farm level. *European Journal of Agronomy* 36, 21–31. doi:10.
801 1016/j.eja.2011.08.003.

802 Gemma, M., Tsur, Y., 2007. The stabilization value of groundwater and con-
803 junctive water management under uncertainty. *Applied Economic Perspec-*
804 *tives and Policy* 29, 540–548. doi:10.1111/j.1467-9353.2007.00366.x.

805 Grantham, T.E., Mezzatesta, M., Newburn, D.A., Merenlender, A.M., 2014.
806 Evaluating tradeoffs between environmental flow protections and agricultural
807 water security. *River Research and Applications* 30, 315–328. doi:10.1002/
808 rra.2637.

809 Grantham, T.E., Viers, J.H., 2014. 100 years of California’s water rights system:
810 patterns, trends and uncertainty. *Environmental Research Letters* 9, 84012–
811 84021. doi:10.1088/1748-9326/9/8/084012.

812 Guilfoos, T., Khanna, N., Peterson, J.M., 2016. Efficiency of viable groundwater
813 management policies. *Land Economics* 92, 618–640. doi:10.3368/le.92.4.
814 618.

815 Harou, J.J., Lund, J.R., 2008. Ending groundwater overdraft in hydrologic-
816 economic systems. *Hydrogeology Journal* 16, 1039–1055. doi:10.1007/
817 s10040-008-0300-7.

818 Hartz, T. Miyao, G., Mickler, J., Lestrangle, M., Stoddard, S., Nunez, J.,
819 Aegerter, B., 2008. Processing tomato production in California. Publication
820 no. 7228. University of California, Davis, California, USA.

821 Hecox, G.R., Macfarlane, P.A., Wilson, B.B., 2002. Calculation of yield for
822 High Plains wells: Relationship between saturated thickness and well yield.
823 Report No.2002-25C. Kansas Geological Survey, Lawrence, KS, USA.

824 Howitt, R.E., MacEwan, D., Medellín-Azuara, J., Lund, J.R., Sumner, D., 2015.
825 Economic analysis of the 2015 drought for California agriculture. UC Davis
826 Center for Watershed Sciences, Davis, California, USA.

827 Howitt, R.E., Medellín-Azuara, J., Lund, J.R., Sumner, D., 2014. Economic
828 analysis of the 2014 drought for California agriculture. UC Davis Center for
829 Watershed Sciences, Davis, California, USA.

830 Katerji, N., Campi, P., Mastrorilli, M., 2013. Productivity, evapotranspiration,
831 and water use efficiency of corn and tomato crops simulated by AquaCrop

under contrasting water stress conditions in the Mediterranean region. Agricultural Water Management 130, 14–26. doi:10.1016/j.agwat.2013.08.005.

Knapp, K.C., Olson, L.J., 1995. The economics of conjunctive groundwater management with stochastic surface supplies. Journal of Environmental Economics and Management 28, 340–356. doi:10.1006/jeem.1995.1022.

Linker, R., Ioslovich, I., Sylaios, G., Plauborg, F., Battilani, A., 2016. Optimal model-based deficit irrigation scheduling using AquaCrop: A simulation study with cotton, potato and tomato. Agricultural Water Management 163, 236–243. doi:10.1016/j.agwat.2015.09.011.

Long, R., Munier, D., Klonsky, K.M., De Moura, R.L., 2012. Sample costs to produce oat hay. University of California Cooperative Extension, Davis, California, USA.

Marques, G.F., Lund, J.R., Howitt, R.E., 2009. Modeling conjunctive use operations and farm decisions with two-stage stochastic quadratic programming. Journal of Water Resources Planning and Management 136, 386–394. doi:10.1061/(ASCE)WR.1943-5452.0000045.

Medellín-Azuara, J., MacEwan, D., Howitt, R.E., Koruakos, G., Dogrul, E.C., Brush, C.F., Kadir, T.N., Harter, T., Melton, F., Lund, J.R., 2015. Hydro-economic analysis of groundwater pumping for irrigated agriculture in California’s Central Valley, USA. Hydrogeology Journal 23, 1205–1216. doi:10.1007/s10040-015-1283-9.

Mehta, V.K., Haden, V.R., Joyce, B.A., Purkey, D.R., Jackson, L.E., 2013. Irrigation demand and supply, given projections of climate and land-use change, in Yolo County, California. Agricultural Water Management 117, 70–82. doi:10.1016/j.agwat.2012.10.021.

Miyao, G., Aegerter, B., Klonsky, K., Stewart, D., 2014a. Sample costs to produce processing tomatoes: furrow irrigated. University of California Cooperative Extension, Davis, California, USA.

860 Miyao, G., Aegerter, B., Klonsky, K., Stewart, D., 2014b. Sample costs to pro-
861 duce processing tomatoes: sub-surface drip irrigated. University of California
862 Cooperative Extension, Davis, California, USA.

863 Noel, J.E., Howitt, R.E., 1982. Conjunctive multibasin management: an opti-
864 mal control approach. *Water Resources Research* 18, 753–763. doi:10.1029/
865 WR018i004p00753.

866 OECD, 2015. Drying Wells, Rising Stakes. Towards Sustainable Agricultural
867 Groundwater Use. OECD, Paris, France.

868 Palanisami, K., Giordano, M., Kakumanu, K.R., Ranganathan, C.R., 2012. The
869 stabilization value of groundwater: evidence from Indian tank irrigation sys-
870 tems. *Hydrogeology Journal* 20, 933–941. doi:10.1007/s10040-011-0793-3.

871 Palazzo, A., Brozović, N., 2014. The role of groundwater trading in spatial water
872 management. *Agricultural Water Management* 145, 40–50. doi:10.1016/j.
873 agwat.2014.03.004.

874 Pfeiffer, L., Lin, C.Y., 2014. Does efficient irrigation technology lead to reduced
875 groundwater extraction? Empirical evidence. *Journal of Environmental Eco-
876 nomics and Management* 67, 189–208. doi:10.1016/j.jeem.2013.12.002.

877 Provencher, B., Burt, O., 1993. The externalities associated with the common
878 property exploitation of groundwater. *Journal of Environmental Economics
879 and Management* 24, 139–158. doi:10.1006/jjeem.1993.1010.

880 Provencher, B., Burt, O., 1994. Approximating the optimal groundwater pump-
881 ing policy in a multiaquifer stochastic conjunctive use setting. *Water Re-
882 sources Research* 30, 833–843. doi:10.1029/93WR02683.

883 Pulido-Velázquez, M., Andreu, J., Sahuquillo, A., 2006. Economic optimization
884 of conjunctive use of surface water and groundwater at the basin scale. *Journal
885 of Water Resources Planning and Management* 132, 454–467. doi:10.1061/
886 (ASCE)0733-9496(2006)132:6(454).

887 Pulido-Velazquez, M., Jenkins, M.W., Lund, J.R., 2004. Economic values for
888 conjunctive use and water banking in southern California. *Water Resources*
889 *Research* 40, W03401. doi:10.1029/2003WR002626.

890 Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., 2016. AquaCrop Version 5.0
891 Reference Manual. Food and Agriculture Organization of the United Nations,
892 Rome, Italy.

893 Ranganathan, C.R., Palanisami, K., 2004. Modeling economics of conjunctive
894 surface and groundwater irrigation systems. *Irrigation and Drainage Systems*
895 18, 127–143. doi:10.1023/B:IRRI.0000040251.52864.7e.

896 Reichard, E.G., Li, Z., Hermans, C., 2010. Emergency use of groundwater as a
897 backup supply: Quantifying hydraulic impacts and economic benefits. *Water*
898 *Resources Research* 46, W09524. doi:10.1029/2009WR008208.

899 Richey, A.S., Thomas, B.F., Lo, M.H., Reager, J.T., Famiglietti, J.S., Voss, K.,
900 Swenson, S., Rodell, M., 2015. Quantifying renewable groundwater stress
901 with GRACE. *Water Resources Research* 51, 5217–5238. doi:10.1002/
902 2015WR017349.

903 Rinaldi, M., Garofalo, P., Rubino, P., Steduto, P., 2011. Processing tomatoes
904 under different irrigation regimes in Southern Italy: agronomic and economic
905 assessments in a simulation case study. *Journal of Agrometeorology* 3, 39–56.

906 Ritchel, M., 2015. California farmers dig deeper for water, sip-
907 ping their neighbors dry. *New York Times* URL: [https://www.nytimes.com/2015/06/07/business/energy-environment/
908 california-farmers-dig-deeper-for-water-sipping-their-neighbors-dry.
909 html?_r=0](https://www.nytimes.com/2015/06/07/business/energy-environment/california-farmers-dig-deeper-for-water-sipping-their-neighbors-dry.html?_r=0).

911 Saak, A.E., Peterson, J.M., 2012. Groundwater pumping by heterogeneous
912 users. *Hydrogeology Journal* 20, 835–849. doi:10.1007/s10040-012-0854-2.

913 Scanlon, B.R., Faunt, C.C., Longuevergne, L., Reedy, R.C., Alley, W.M.,
914 McGuire, V.L., McMahon, P.B., 2012. Groundwater depletion and sustain-

915 ability of irrigation in the US High Plains and Central Valley. *Proceedings*
916 *of the National Academy of Sciences* 109, 9320–9325. doi:10.1073/pnas.
917 1200311109.

918 Scanlon, B.R., Reedy, R.C., Faunt, C.C., Pool, D., Uhlman, K., 2016. Enhanc-
919 ing drought resilience with conjunctive use and managed aquifer recharge
920 in California and Arizona. *Environmental Research Letters* 11, 035013.
921 doi:10.1088/1748-9326/11/4/049501.

922 Schewe, J., Heinke, J., Gerten, D., Haddeland, I., Arnell, N.W., Clark, D.B.,
923 Dankers, R., Eisner, S., Fekete, B.M., Colón-González, F.J., et al., 2014.
924 Multimodel assessment of water scarcity under climate change. *Proceedings*
925 *of the National Academy of Sciences* 111, 3245–3250. doi:10.1073/pnas.
926 1222460110.

927 Schoups, G., Addams, C.L., Minjares, J.L., Gorelick, S.M., 2006. Sustainable
928 conjunctive water management in irrigated agriculture: Model formulation
929 and application to the Yaqui Valley, Mexico. *Water Resources Research* 42,
930 W10417. doi:10.1029/2006WR004922.

931 Seager, R., Ting, M., Li, C., Naik, N., Cook, B., Nakamura, J., Liu, H., 2013.
932 Projections of declining surface-water availability for the southwestern United
933 States. *Nature Climate Change* 3, 482–486. doi:10.1038/nclimate1787.

934 Singh, A., 2014. Conjunctive use of water resources for sustainable irrigated
935 agriculture. *Journal of Hydrology* 519, 1688–1697. doi:10.1016/j.jhydrol.
936 2014.09.049.

937 Steduto, P., Hsiao, T.C., Raes, D., Fereres, E., 2009. AquaCrop - The FAO crop
938 model to simulate yield response to water: I. concepts and underlying princi-
939 ples. *Agronomy Journal* 101, 426–437. doi:10.2134/agronj2008.0139s.

940 Taylor, R.G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y.,
941 Longuevergne, L., Leblanc, M., Famiglietti, J.S., Edmunds, M., et al., 2013.

942 Ground water and climate change. *Nature Climate Change* 3, 322–329.
 943 doi:10.1038/nclimate1744.

944 Thompson, C.L., Supalla, R.J., Martin, D.L., McMullen, B.P., 2009. Evidence
 945 supporting cap and trade as a groundwater policy option for reducing irriga-
 946 tion consumptive use1. *Journal of the American Water Resources Association*
 947 45, 1508–1518. doi:10.1111/j.1752-1688.2009.00384.x.

948 Tsur, Y., 1990. The stabilization role of groundwater when surface water sup-
 949 plies are uncertain: The implications for groundwater development. *Water*
 950 *Resources Research* 26, 811–818. doi:10.1029/WR026i005p00811.

951 Tsur, Y., 1997. The economics of conjunctive ground and surface water, in:
 952 Parker, D., Tsur, Y. (Eds.), *Decentralization and coordination of water re-*
 953 *source management*. Kulwer, London, UK.

954 Tsur, Y., 2015. Conjunctive management of water resources in agriculture, in:
 955 Dinar, A., Schwabe, K. (Eds.), *Handbook of Water Economics*. Edward Elgar
 956 Publishing, Cheltenham, UK.

957 Tsur, Y., Graham-Tomasi, T., 1991. The buffer value of groundwater with
 958 stochastic surface water supplies. *Journal of Environmental Economics and*
 959 *Management* 21, 201–224. doi:10.1016/0095-0696(91)90027-G.

960 U.S. Bureau of Reclamation, 2016. Summary of water supply allocations.
 961 URL: [https://www.usbr.gov/mp/cvo/vungvari/water_allocations_](https://www.usbr.gov/mp/cvo/vungvari/water_allocations_historical.pdf)
 962 [historical.pdf](https://www.usbr.gov/mp/cvo/vungvari/water_allocations_historical.pdf).

963 Veshkin, A., 2015. Dry wells plague California as
 964 drought has water tables plunging. Bloomberg URL:
 965 [https://www.bloomberg.com/news/articles/2015-04-17/](https://www.bloomberg.com/news/articles/2015-04-17/california-plagued-by-dry-wells-as-drought-makes-water-elusive)
 966 [california-plagued-by-dry-wells-as-drought-makes-water-elusive](https://www.bloomberg.com/news/articles/2015-04-17/california-plagued-by-dry-wells-as-drought-makes-water-elusive).

967 Ward, F.A., Pulido-Velazquez, M., 2008. Water conservation in irrigation can
 968 increase water use. *Proceedings of the National Academy of Sciences* 105,
 969 18215–18220. doi:10.1073/pnas.0805554105.

970 Wheeler, S.A., Schoengold, K., Bjornlund, H., 2016. Lessons to be learned
971 from groundwater trading in australia and the united states, in: Jakeman,
972 A.J., Barreteau, O., Hunt, R.J., Rinaudo, J.D., Ross, A. (Eds.), Integrated
973 Groundwater Management. Springer, pp. 493–517.