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Growing farms and groundwater depletion in the Kansas High Plains

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Growing farms and groundwater depletion in the Kansas High Plains

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E-mail: lmarston@vt.edu**Keywords:** farm size, farm structure, rebound effect, groundwater, aquifer, irrigation efficiency, High PlainsSupplementary material for this article is available [online](#)**Abstract**

The average farm size has more than doubled within the United States over the last three decades, transforming the agricultural industry and rural farming communities. It is unclear, however, how this ubiquitous trend has affected and is affected by the environment, particularly groundwater resources critical for food production. Here, we leverage a unique multi-decadal dataset of well-level groundwater withdrawals for crop irrigation over the Kansas High Plains Aquifer to determine the interactions between groundwater depletion and growing farms. Holding key technological, management, and environmental variables fixed, we show that doubling a farm's irrigated cropland decreases groundwater extractions by 2%–5% depending on the initial farm size. However, a corresponding shift by larger farms to different irrigation technologies offsets this reduction in groundwater use, leading to a slight increase in overall groundwater use. We find groundwater depletion increases the likelihood farmland is sold to a larger farm, amplifying the cycle of groundwater depletion and the consolidation of farmland.

1. Introduction

Small and mid-sized farm operations within the United States have been increasingly consolidated into larger farms (>800 ha; MacDonald *et al* 2018, figure S1 (available online at stacks.iop.org/ERL/16/084065/mmedia)). These large farms now comprise one-third of all US harvested cropland, more than quadrupled from three decades prior (MacDonald *et al* 2018). At the same time, the share of small and mid-sized farms (40–200 hectares) has fallen from 40% to 20% (MacDonald *et al* 2018). Moreover, only 6% of the over 2 million US farms produce three-quarters of all agriculture output (Sumner 2014). This structural change within the agricultural sector is expected to continue in the United States, as well as other high-income countries (Rada and Fuglie 2019).

Previous studies have identified labor-saving technological innovations, farm specialization, and government policies as some of the underlying drivers of farmland consolidation. Together, these

underlying drivers enable larger farms to exploit constant or increasing returns of scale to improve productivity (Kislev and Peterson 1982, Morrison Paul *et al* 2004, Key 2019, Rada and Fuglie 2019). Labor-saving innovations, such as mechanical farm equipment, pesticides, genetically engineered seeds, and precision technologies, reduce the required labor hours per hectare, potentially freeing producers to manage larger farms (Kislev and Peterson 1982, MacDonald *et al* 2013). Tax policies and government research programs can lower costs of capital and technology, potentially leading to greater investments in labor-saving innovations that also enable larger farms (MacDonald *et al* 2013). Broad-based commodity programs and insurance absorb some of the financial risk in growing certain field crops, thereby permitting greater levels of specialization, investments in commodity-specific equipment, and access to capital—all precursors to cropland expansion (Westcott and Price 2001, Roberts and Key 2008, MacDonald *et al* 2013). These technological, policy,

and market-based drivers of cropland consolidation explain the societal forces behind this ubiquitous trend. However, it is unclear how or if environmental conditions, such as groundwater depletion, also contribute to the consolidation of cropland.

A complicated mix of local and nonlocal factors contribute to groundwater depletion, making groundwater resources challenging to sustainably manage. Local environmental conditions, such as aquifer thickness, recharge, hydraulic conductivity, depth to water table, specific yield, surface drainage, and precipitation, strongly influence the degree to which producers pump groundwater (Heath 1983). Likewise, local social factors like a neighbor's irrigation schedule or crop planting decisions can also influence groundwater withdrawals (Pfeiffer and Lin 2012, National Agricultural Statistics Service 2014, Sampson and Perry 2018). Producers are embedded within a global food system, such that national subsidies (Deryugina and Konar 2017), international trade policies and tariffs (Dalin *et al* 2012), and global commodity prices (Marston and Konar 2017) can indirectly influence water use for irrigation. Determining the relationship between groundwater pumping, aquifer depletion, and structural changes in farming operations can help us understand the broader systematic factors shaping both farm size and groundwater overexploitation.

In this study, we answer two interrelated questions about the linkages between structural change in the agriculture sector and the utilization of natural resources with a Kansas case study. More specifically, we focus on the potential feedbacks between groundwater use and depletion and the expansion—primarily via consolidation—of irrigated cropland by asking: (a) Does a farm's expansion of irrigated cropland lead to a reduction in their intensity of groundwater use? and (b) Does an increase in the rate of groundwater depletion increase the likelihood irrigated cropland is transferred into the operation of a larger farm? We answer these questions using a two-way fixed effects (FE) model and a correlated random effects (RE) model, respectively. These models were developed on a unique multi-decadal dataset of well-level groundwater withdrawals by irrigators over the Kansas High Plains Aquifer. Our research improves our understanding of how broad structural changes within the agricultural industry are interconnected with the overexploitation of groundwater resources.

2. Methods

2.1. Data

2.1.1. Groundwater well dataset

A geo-spatially referenced dataset from the Kansas Department of Agriculture's Division of Water Resources and Kansas Geological Survey (KGS), called Water Information Management and Analysis System (WIMAS) program (Wilson *et al* 2005), is

used to develop the empirical models used in this study. The Kansas Water Appropriation Act (Rogers *et al* 2013) requires the installation of state approved flowmeters on all irrigation wells and the reporting of annual water use for each point of diversion. Since the penalties of failure to report water use (even when no water was used that year) was added to the water appropriation act in the early 1990s, around 93% of all water users now report their annual water use (KDA 2020). Irrigators also report irrigated acreage, crop type, and irrigation system, which are all recorded in the WIMAS database (Wilson *et al* 2005). We assigned each groundwater well to the person who filed the water use report for that well. That is, we assume that the person making the operational decisions is most likely to know the amount of water applied and report that information to the state for all the wells they operate. Irrigated farm size is calculated as the sum of irrigated acres across all wells for a given irrigator (who is the operator/manager of all the irrigated land of those wells, but not necessarily the owner of all the land). Climate data from PRISM (2004), monitoring well data from KGS (2018b), and crop yield and producer price time series data from US Department of Agriculture (USDA) (NASS 2009) were also used to compile the complete dataset.

We restrict our analysis on the well-year combinations where (a) the well is located within the High Plains Aquifer extent and pumps from a groundwater source, and (b) water use is measured by state certified flowmeters (as opposed to being estimated by the irrigator). To reduce the effect of outliers, which may reflect faulty meters or erroneous reporting, for example, we exclude records that are 1.5 times the inter-quartiles range outside the 1st quartile and 3rd quartile range for groundwater irrigation depth, as well as total irrigated cropland of the irrigator. Furthermore, only wells with 90% or more continuity of valid records after the filters described above remained in our analysis. This combined and cleaned dataset contains approximately 216 000 well-level observations across 17 126 individual wells in the Kansas part of the High Plains Aquifer during 1993–2014 (see table S1 for additional data details and figure 1 for data spatial coverage).

2.1.2. Aquifer thickness dataset

Bedrock elevation contour lines (Kansas Geological Survey 2018a) and the High Plains Aquifer phreatic surface (produced using monitoring well readings from the KGS's Water Information Storage and Retrieval Database (WIZARD) dataset (Kansas Geological Survey 2018b) were combined into a series of raster files, which together provide an estimate of the aquifer thickness at each pumping well. Wells belonging to a different aquifer than the High Plains Aquifer, such as the Arkansas River alluvial aquifer, were excluded. Only monitoring records during January, February, and March were used, as the

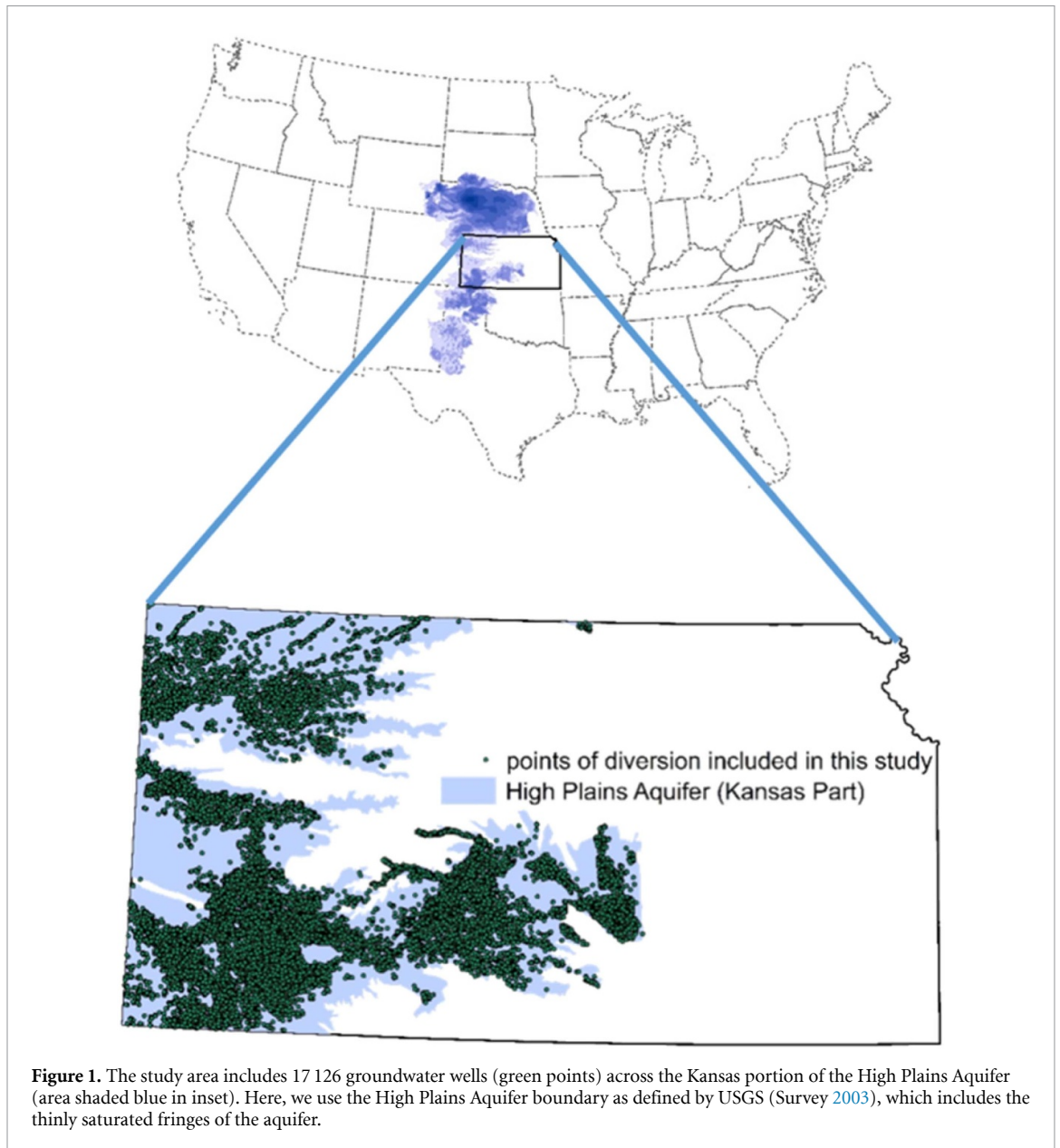


Figure 1. The study area includes 17 126 groundwater wells (green points) across the Kansas portion of the High Plains Aquifer (area shaded blue in inset). Here, we use the High Plains Aquifer boundary as defined by USGS (Survey 2003), which includes the thinly saturated fringes of the aquifer.

water table is typically more stable during this period. The difference between the annually varying water table elevation and bedrock elevation (assumed to be constant throughout the study period) equals the aquifer thickness at the pumping well location for a given year. Only valid records were maintained in the final dataset (e.g. bedrock levels reported above the ground surface were removed). The final set of wells assigned aquifer thickness values, as well as other previously described associated data, contained over 157 000 records. These records were used in the models described by equations (3) and (4) below.

2.2. Irrigated cropland expansion effect on irrigation depth

Our approach estimates the relationship between a farm's expansion of irrigated cropland and its groundwater withdrawals. We do this by exploiting

how withdrawals changed differently for wells managed by producers that had a change in farm size (i.e. irrigated cropland holdings) compared to those that did not.

We estimate how farm expansion of irrigated cropland impacts applied irrigation by taking advantage of multi-year observations of how applied water changed differently for different changes in farm size across wells. To capture variation across time and space, we used a two-way FE model that includes both well and year-specific intercepts. Our FE model to estimate the direct effect on irrigation depth is as follows:

$$w_{it} = \ln(\text{Size}_{it})\beta_1 + \mathbf{X}'_{it}\gamma_1 + \mathbf{Z}'_{it}\gamma_2 + \alpha_i + \delta_t + \varepsilon_{it} \quad (1)$$

where w_{it} is the irrigation application rate (millimeter (mm)) for well i reported for year t . $\ln(\text{Size}_{it})$

is the natural logarithm of total irrigated area for the producer operating well i in given year t . The natural log is taken to account for the skewed distribution of irrigated farm size. \mathbf{X}_{it} is a vector of control variables, which include quarterly reference evapotranspiration, quarterly precipitation, and each crop's county-level revenue per unit area. \mathbf{Z}_{it} denotes a set of land use controls that include crop type and irrigation technology. The land use controls include a set of seven binary variables to indicate the irrigation system (i.e. the seven irrigation technologies listed in table 1, plus 'other systems' which serves as the baseline of comparison within our model). Each crop type (corn, wheat, soybean, sorghum, alfalfa, and other) and their combinations grown within the study area are represented as a binary variable within our model. α_i is a well-FE, a well-specific intercept that allows us to control a well's time-invariant characteristic such as soils. δ_t is the year-FE that accounts for factors that change over time that are the same across wells such as farm programs, energy and input prices, and crop prices. Finally, ε_{it} is the error term. β_1 , γ_1 , and γ_2 are vectors of coefficients corresponding to each of the variables.

We assume that there are no omitted variables that change over time differently for different wells that are correlated with changes in both irrigated farm size and irrigation depth. Under this assumption, the model coefficients in equation (1) are unbiased. Note that our coefficient and standard error estimates are unbiased even if there is measurement error in the water use data due to errors in the flowmeter data because these meter errors are unlikely to be systematically correlated with irrigated farm size. Standard errors are clustered by wells to account for correlation in the error for a given well over time and allow different variances across wells.

We capture variation across time and space by including a unique intercept/constant for each well and a unique intercept/constant for each year in the regression model, equivalent to controlling for immeasurable factors specific to the well and the year (among other variables explicitly included) that could possibly lead to changes in both the owner farm size and irrigation depth. These unique intercepts for each well and year are commonly referred to as 'fixed effects' in the economics literature (Wooldridge 2010, Hendricks and Peterson 2012). The well-specific intercepts control for the spatial variation in water applied and farm size that could be due to confounding variables. For example, regions with poor soils may have smaller farm sizes and also apply more water. The year-specific intercepts control for the relationship in water applied and farm size over time that could be due to confounding variables such as crop prices or federal government policy. Intuitively, our model exploits how changes in an operator's total irrigated area over time impacts the change in irrigation depth applied at that well.

Once the model coefficients are established using all well observations, we investigate the change in irrigated depth $\{w_{it} - w_{i,t-1}\}$ due to the expansion of a producer's irrigated cropland $\left\{ \ln(\text{Size}_{it}) - \ln(\text{Size}_{i,t-1}) \right\}$ or, alternatively, $\ln\left(\frac{\text{Size}_{it}}{\text{Size}_{i,t-1}}\right)$. Note that $\ln\left(\frac{\text{Size}_{it}}{\text{Size}_{i,t-1}}\right)$ is equivalent to the natural log of the sum of a farm's rate of irrigated cropland expansion between year t and $t - 1$ and one. We calculated the average farm expansion rate of irrigated cropland for well records that showed an increase in irrigated farm size from one year to the next, then we used the estimated model coefficients to determine the corresponding average change in irrigation depth due to this average expansion in farm size. That is, in the year these farms increased their irrigated cropland their average single year growth rate was calculated by summing their growth rates (with farms having more wells weighted more) and then dividing this sum by the number of well records that belonged to these growing farms.

We estimate the total effect of farm size on irrigation depth using the following FE model:

$$w_{it} = \ln(\text{Size}_{it})\beta_2 + \mathbf{X}'_{it}\gamma_1 + \alpha_i + \delta_t + \varepsilon_{it}. \quad (2)$$

Note that equation (2) omits the land use controls (\mathbf{Z}'_{it}) that were included in equation (1).

The FE models (equations (1) and (2) above) control for time-invariant heterogeneity across wells (e.g. soils) and time-dependent factors that affect all wells (e.g. energy prices) by including well-specific and year-specific intercepts. The key dependent variable is the irrigation depth, a measure of irrigation intensity, defined as volume of irrigation water applied divided by irrigated area. The 'direct effect' in equation (1) holds constant the land use, while the 'total effect' in equation (2) allows land use to also change as farm size changes. The *total effect* represents the expected change in the intensity of groundwater use due to growing irrigated farm size. The total effect encompasses both the direct and indirect effects. The *direct effect* also represents the change in the intensity of groundwater use due to growing irrigated farm size; however, the direct effect holds crop type and irrigation technology constant (both of which have a significant impact on irrigation withdrawals and might also be impacted by farm size growth) to better understand the source of the change in groundwater use due to a irrigated cropland expansion. Put differently, the direct effect is the unmediated impact of the farm size change on irrigation water depth that cannot be explained by the adjustments of any of the control variables. The difference between the total and direct effects is the indirect effect of irrigated farm size on irrigation depth through changes in the crop type and irrigation system (Hendricks and Peterson 2012). The *indirect effect* is the change in groundwater irrigation applications due to adjustments in irrigation

Table 1. Regression results for two-way fixed effects models of total effect and direct effect of changes in irrigated farm size on change in irrigation depth. Values not in parentheses are the regression coefficients associated with each variable and represent the expected change in irrigation depth (dependent variable; mm) for a one unit increase in this variable. Note that for the natural log of farm total irrigated hectares the coefficient represents change in withdrawal (mm) that corresponds to one unit change in the natural log of the irrigated area, instead of simply a 1 hectare change in the area. Negative regression coefficients indicate the dependent and independent variable have an inverse relationship, while a positive coefficient value indicates a positive relationship. The standard error associated with each variable is a measure of statistical precision of the estimated direction and magnitude of the relationship and is shown in parentheses.

Variable	Total effect model	Direct effect model
ln (farm total irrigated hectares)	1.574*** (0.534)	−10.472*** (0.586)
Irrigation Tech.: flood	—	55.041*** (7.146)
Irrigation Tech.: drip (subsurface irrigation)	—	−10.086 (8.539)
Irrigation Tech.: center pivot sprinkler	—	7.660 (7.091)
Irrigation Tech.: center pivot sprinkler w/drop nozzles	—	13.745* (7.067)
Irrigation Tech.: sprinkler other than center pivot	—	−10.897 (8.298)
Irrigation Tech.: center pivot and flood	—	11.663 (7.092)
Irrigation Tech.: drip and other systems	—	−0.671 (9.830)
Precipitation (mm): Jan–Mar	−0.093*** (0.013)	−0.084*** (0.014)
Precipitation (mm): Apr–Jun	−0.192*** (0.006)	−0.234*** (0.006)
Precipitation (mm): Jul–Sep	−0.153*** (0.005)	−0.192*** (0.006)
Precipitation (mm): Oct–Dec	−0.159*** (0.009)	−0.166*** (0.010)
Reference evapotranspiration (mm): Jan–Mar	0.902*** (0.058)	1.071*** (0.063)
Reference evapotranspiration (mm): Apr–Jun	0.569*** (0.034)	0.605*** (0.037)
Reference evapotranspiration (mm): Jul–Sep	0.307*** (0.035)	0.310*** (0.037)
Reference evapotranspiration (mm): Oct–Dec	−0.795*** (0.074)	−0.718*** (0.081)
Revenue (\$ hectare ^{−1}): alfalfa	0.414*** (0.131)	−0.428*** (0.140)
Revenue (\$ hectare ^{−1}): corn	0.049*** (0.008)	0.014 (0.009)
Revenue (\$ hectare ^{−1}): sorghum	−0.031*** (0.008)	−0.039*** (0.009)
Revenue (\$ hectare ^{−1}): soybean	0.066*** (0.014)	0.044*** (0.015)
Revenue (\$ hectare ^{−1}): wheat	−0.143*** (0.0156)	−0.136*** (0.017)
Year-specific intercepts	Yes	Yes
Well-specific intercepts	Yes	Yes
Crop choice controls	No	Yes
Response of irrigation depth (mm) to doubling of farm total irrigated hectares	1.1 ^a	−7.3 ^a

Standard errors in parenthesis.

*** $p < 0.01$, * $p < 0.1$.

^a Note that the coefficient on the log of farm total irrigated hectares is the impact of a 1% change in farm size. We calculate the effect of doubling farm total irrigated hectares as the coefficient times $\ln(2)$ because $\ln(2x) - \ln(x) = \ln(2)$, for any given farm size x . The 1.1 mm increase in average irrigation depth associated with the total effect represents a 0.34% increase from initial average irrigation depths, while the 7.3 mm reduction associated with the direct effect represents a 2.3% decrease.

management (i.e. a different irrigation system or a different choice of crop(s)) corresponding to a transfer in farm ownership or operation (see figure 2 for an illustration of the relationship between direct effect, indirect effect, and total effect).

The direct effect estimated as β_1 in equation (1) represents the change in applied irrigation depth due to a change in irrigated farm size, holding constant the cropping patterns and irrigation technology. The total effect estimated as β_2 in equation (2) represents the change in applied irrigation depth due to a change in irrigated farm size allowing for potential changes in cropping patterns and irrigation technology related to changes in irrigated farm size. The indirect effect can be calculated as the difference between the total effect and the direct effect ($\beta_2 - \beta_1$). The indirect effect represents the change in applied irrigation

depth through the pathway of land use adjustment (i.e. change in crop choice and/or irrigation technology).

2.3. Groundwater depletion effect on farm consolidation

We analyze how aquifer depletion in previous years impacts the probability of changing the manager (i.e. a change in ownership or tenancy) using a correlated RE model with a probit link function (equation (3)). Including FE creates bias in non-linear models where the dependent variable is binary, such as a probit model. A common solution is to use the correlated RE model as a method to control for unobserved time-invariant variables while avoiding the bias from including FE (Wooldridge 2010). Our probit model is specified as

$$MC_{it} = \Phi \left(\frac{\mu_1 \overline{Sat_{i,t-1}} + \mu_2 \overline{\Delta Sat_{i,t-1 \text{ to } t}} + \mu_3 \overline{Sat_{i,t-1}} \times \overline{\Delta Sat_{i,t-1 \text{ to } t}} + X'_{it} \gamma_1 + Z'_{it} \gamma_2 + \theta_1 \overline{Sat_{i,t-1}} + \theta_2 \overline{\Delta Sat_{i,t-1 \text{ to } t}} + \theta_3 \overline{Sat_{i,t-1}} \overline{\Delta Sat_{i,t-1 \text{ to } t}} + \overline{X'_{it}} \gamma_3 + \overline{Z'_{it}} \gamma_4 + \delta_t + \varepsilon_{it}}{\theta_1 \overline{Sat_{i,t-1}} + \theta_2 \overline{\Delta Sat_{i,t-1 \text{ to } t}} + \theta_3 \overline{Sat_{i,t-1}} \overline{\Delta Sat_{i,t-1 \text{ to } t}} + \overline{X'_{it}} \gamma_3 + \overline{Z'_{it}} \gamma_4 + \delta_t + \varepsilon_{it}} \right) \quad (3)$$

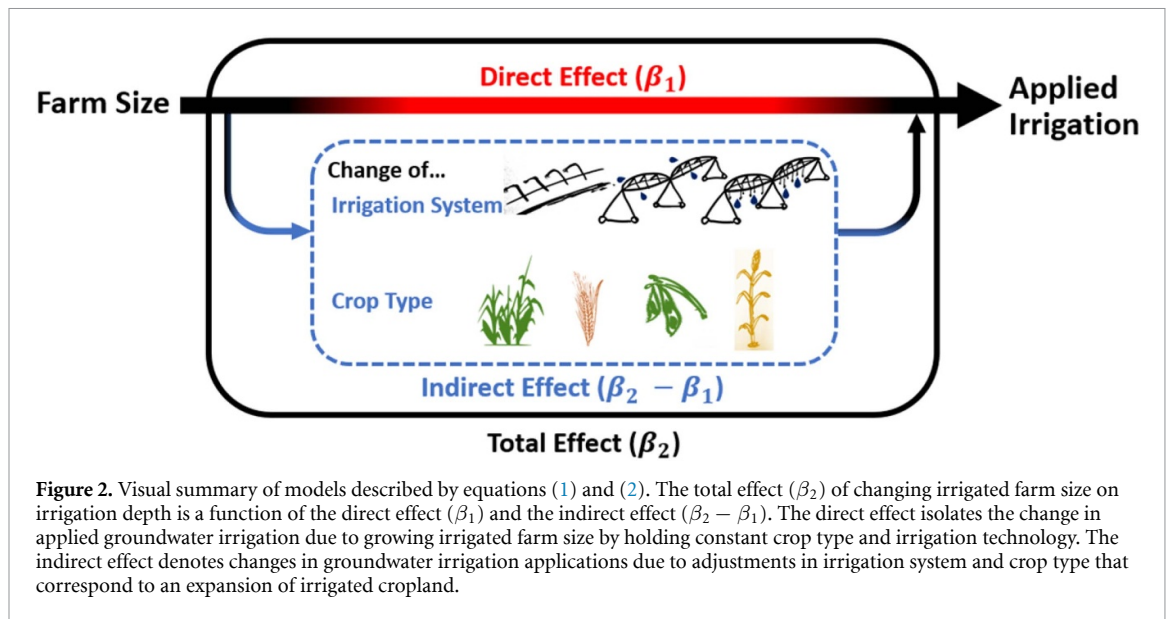
where MC_{it} is equal to 1 if year $t + 1$'s manager/irrigator is different than year t . $\Phi(\cdot)$ is the cumulative standard normal distribution function. $Sat_{i,t-1}$ is the aquifer thickness in year $t - 1$ while $\Delta Sat_{i,t-1}$ is the change in aquifer thickness (i.e. the depletion rate in m yr^{-1} , which is positive if there is reduction of thickness) from year $t - 1$ to year t . The variables with overlines are the mean values of the corresponding variable for each cross-sectional unit/well i ; this is to effectively control for time-invariant unobserved heterogeneity (Wooldridge 2010). δ_t is the year specific intercept. The coefficients accompanying variables θ_1 to θ_3 and γ_1 to γ_4 do not have a causal interpretation but are rather a way of controlling for observed and unobserved heterogeneity.

The transfer probability (i.e. MC_{it}) is the likelihood that a well is owned or operated by a new person the following year. μ_1 is a coefficient that relates an aquifer thickness to the transfer probability, μ_2 relates the annual change in aquifer thickness to the transfer probability, and μ_3 provides information on whether the aquifer thickness and annual change in aquifer thickness act in coordination when predicting transfer probabilities. If an interaction term between two independent variables has a coefficient (i.e. μ_3) estimate that is statistically significant, it indicates that the influence of one of the two independent variables on the dependent variable depends on the value of the other independent variable. In the context of our model, a statistically significant interaction term, μ_3 , means that the annual change (from year $t - 1$ to t) in aquifer thickness' influence on the transfer

probability depends on the aquifer thickness in year $t - 1$. Estimates of μ_1 and μ_2 cannot be easily interpreted directly due to model non-linearity. Therefore, to determine the marginal effect of changes in $Sat_{i,t-1}$ and $\Delta Sat_{i,t-1 \text{ to } t}$ (corresponding to μ_1 and μ_2 , respectively) all other variables were first set to their mean, which is commonly referred to as the marginal effect at the means.

To explore the differences between wells of differentiated long-term depletion conditions, we divided the records into four subsets based on their long-term average annual depletion rate during the study period: none/mild ($<0.1 \text{ m yr}^{-1}$), moderate ($0.1\text{--}0.5 \text{ m yr}^{-1}$), severe ($0.5\text{--}1.0 \text{ m yr}^{-1}$), very severe ($>1.0 \text{ m yr}^{-1}$). We determine the probability that the irrigated cropland is transferred to another owner/operator for each depletion class for all levels of aquifer thickness using the model described by equation (3). The expected transfer probability and associated 95% confidence intervals (CIs) were calculated as well.

Lastly, we determine if the overall trend in irrigated cropland transfers is toward more fragmented smaller holdings or larger farm holdings. To determine this trend, we isolated well records if the well and corresponding irrigated cropland were identified as having an elevated probability of being transferred due to the underlying aquifer thickness and a change in farm management was actually observed (i.e. $MC_{it} = 1$). Using equation (3), we calculate the probability of transferring management under the observed aquifer thickness versus the transfer



probability if the aquifer thickness is one meter thicker. For this subset of well records, the ratio between the current and previous irrigated farm size (SR) is calculated as below:

$$SR = \exp \left[\frac{1}{N} \sum \ln \left(\frac{Size_{i,t+1}}{Size_{i,t}} \right) \right] \quad (4)$$

where N is the total number of observations in the filtered dataset. We introduce the natural logarithm to minimize the impact of outliers. If SR is larger than 1.0, it indicates that on average, a transfer of irrigated land attributable to groundwater depletion will result in a larger operator.

3. Results

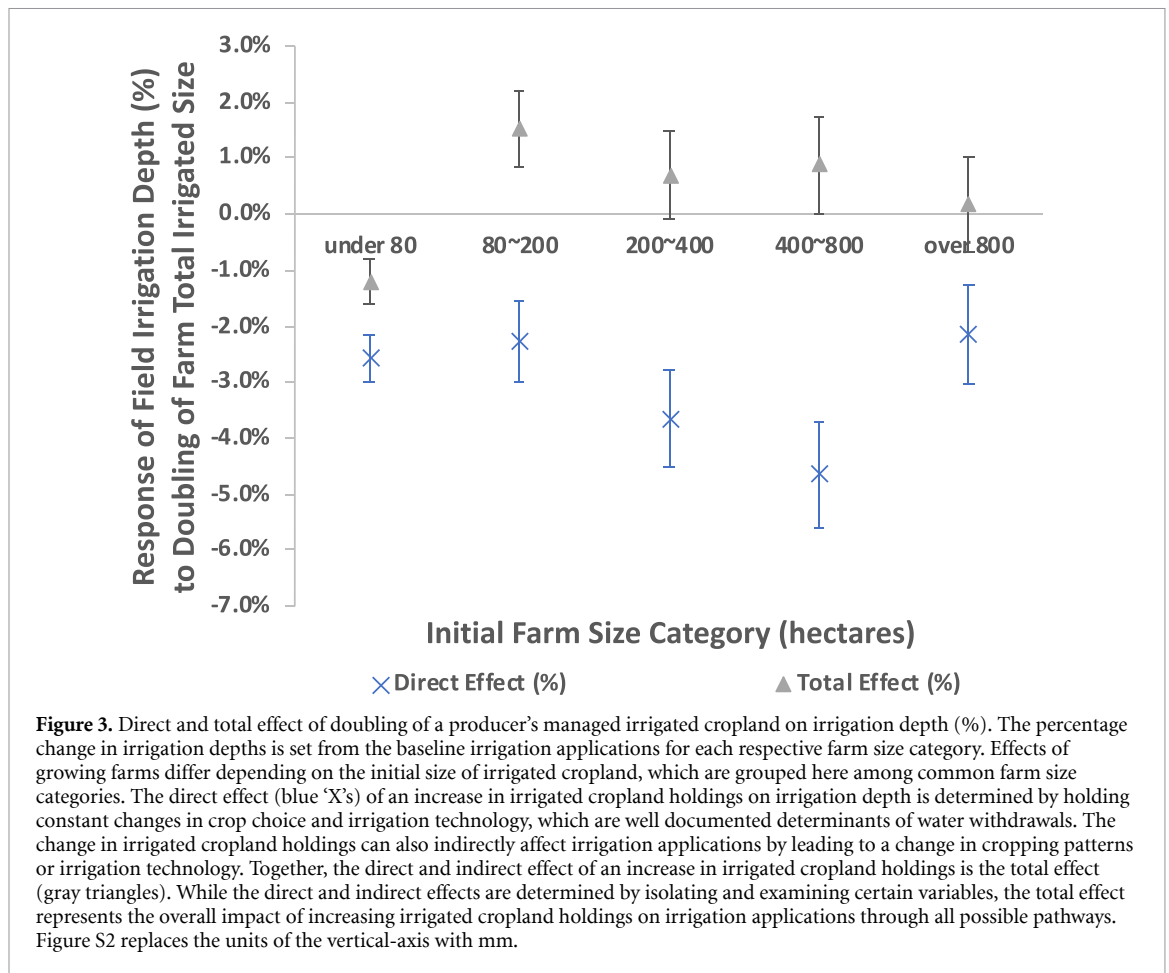
3.1. Irrigated cropland expansion effect on groundwater irrigation

When a farm expands its irrigated cropland, the total effect of increased irrigated farm size is an increase in groundwater use per hectare (i.e. irrigation depth in table 1). If a farm were to double its irrigated cropland, on average it would use 0.34% (1.1 mm) more groundwater per year. However, the average total effect masks differences in the effect on groundwater use between different initial farm sizes. After grouping farms by their initial farm size (roughly following the farm size categories of the USDA (MacDonald et al 2013, 2018, Key 2019)), we find that the smallest farms (0–80 hectares) use 1.2% less groundwater due to a doubling in size (figure 3). However, the next smallest farm size category (80–200 hectares) use 1.5% more groundwater due to a doubling of the operator's total irrigated cropland holdings. The magnitude and direction (from a decrease in pumping to an increase in pumping) of the change between these two initial farm size categories suggest that groundwater pumping in these small-

medium-sized farms is the most sensitive to changes in farm size.

Farms that increased their irrigated cropland from one year to the next grew by 49% from the previous year, on average. This increase in farm size led to an average 4.2 mm (1.3%) decrease (direct effect, 95% CI: 3.7–4.6 mm) in applied irrigation depth holding constant technology and cropping patterns (table S2). However, the increase in irrigated cropland holdings also led to changes in farm irrigation technology and cropping patterns. Taken together, the increase in farm size and corresponding changes in irrigation technology and cropping patterns (i.e. total effect) led to an average increase of 0.6 mm (0.2%) in irrigation applications (CI: 0.2–1.1 mm). If we evaluate rates of farm expansion based on initial farm size, the average expansion in irrigated cropland varies between 22% and 83%, with smaller farms seeing larger relative growth than larger farms. Table S2 shows the average growth rate by initial farm size, as well as the associated direct and total effect of operating more irrigated cropland on irrigation applications. Since the average growth in farm size is dependent on both the initial farm size and the length of records, we use a standard increase of 100% (i.e. doubling of irrigated cropland) to provide a more uniform assessment of the impact of increasing an operator's irrigated cropland on irrigation depths (figure 3).

The direct effect of farm expansion of irrigated cropland is a reduction in groundwater use. Overall, when all farm size categories are considered together, a doubling of the average farm size leads to 7.3 mm (2.3%; 95% CI: 6.5–8.1 mm) reduction in irrigation depth when holding every other factor constant. Under the average farm size growth rate (49%) during the study period, increasing irrigated cropland holdings directly reduced groundwater irrigation depths by 4.2 mm (1.3%; 95% CI: 3.7–4.6 mm).



The initial size of a farm strongly dictates the direct effect of increasing its irrigated cropland holdings on pumping reductions. While all farm size categories show a decline in groundwater applications as irrigated cropland increases (figure 3, direct effect), medium/large-sized farms show the greatest reduction in groundwater irrigation depths (4.6% reduction with doubling of irrigated cropland), while the smallest and largest farm holdings exhibit a smaller reduction in groundwater irrigation depths (2.1% and 2.6%, respectively). This suggests that there is some threshold of farm size whereby approaches to reduce groundwater pumping become viable but after these improvements are made, further improvements are more limited.

Irrigation efficiency gains through improved management (direct effect) are offset by an increase in irrigation applications associated with a switch in irrigation technology (indirect effect). Figure S3 shows that producers in the study area have shifted from flood and traditional center pivot system to drop nozzle center pivots over the last several decades. An increase in irrigated farm size results in an increased probability of switching to drop nozzle center pivot systems ($p < 0.05$) and a corresponding decrease in traditional center pivot ($p < 0.001$; see SI section 1.2). As shown in table 1, a switch

from flood to drop nozzle center pivot systems is associated with a decrease in applied irrigation. However, there was a greater conversion from traditional center pivot to drop nozzle center pivots than flood to drop nozzle center pivots, which was associated with a net increase in groundwater withdrawals. Drop nozzle center pivot systems are approximately 2% more efficient than traditional center pivot systems (Perry 2006), yet we find that the switch to drop nozzle irrigation actually increases irrigation applications (table 1, $p < 0.1$). Our data did not conclusively show that growing farms have a greater tendency to switch to water-intensive crops. There was a slight increase in irrigated area after the land was transferred, however.

3.2. Groundwater depletion effect on cropland consolidation

We find that the probability of a field transferring to a different operator is greater when there is less aquifer thickness available at the well's location in the aquifer. The median farm transfer is 53 hectares, but transfers range from a few hectares to almost 900 hectares. When evaluated at the average condition (all variables set to their mean values), an irrigated parcel has a 3.91% probability of being transferred. One less meter of aquifer thickness in the previous

Table 2. Regression results showing groundwater depletion’s marginal effect on the transfer of irrigated farmland. The last row provides the baseline probability the irrigated cropland is transferred to a new owner/operator between year t and $t + 1$ (transfer probability, established at average conditions). The preceding rows show the marginal transfer probability from this baseline. Fields whose underlying aquifer thickness is less than the average thickness have a higher probability of being transferred the next year, as indicated by the negative marginal effect of aquifer thickness. There is not sufficient evidence to conclude whether the annual rate of depletion affects the probability of farmland transfers ($p > 0.1$). This is true irrespective of the level of aquifer thickness (interaction term has $p > 0.1$).

Variable	Coefficient estimate	MEM ^a	Standard error of MEM	95% confidence interval	
				Lower	Upper
Aquifer thickness in year $t - 1$ (m)	-0.00617***	-0.053%	0.019%	-0.090%	-0.016%
Annual rate of depletion, year $t - 1$ to year t (m yr ⁻¹)	0.00725	-0.006%	0.028%	-0.061%	0.049%
Interaction of aquifer thickness and annual rate of depletion	-0.000201	—	—	—	—
Response variable predicted value at average conditions					
Transfer probability (unitless)		3.91%	0.20%	3.52%	4.29%

*** $p < 0.01$, * $p < 0.1$.

^a Marginal effect at means (MEM) is the change of the response variable (i.e. here, the probability of farmland transfer) upon one unit change of predictor variable (e.g. aquifer thickness), when all other variables are held constant at the average conditions.

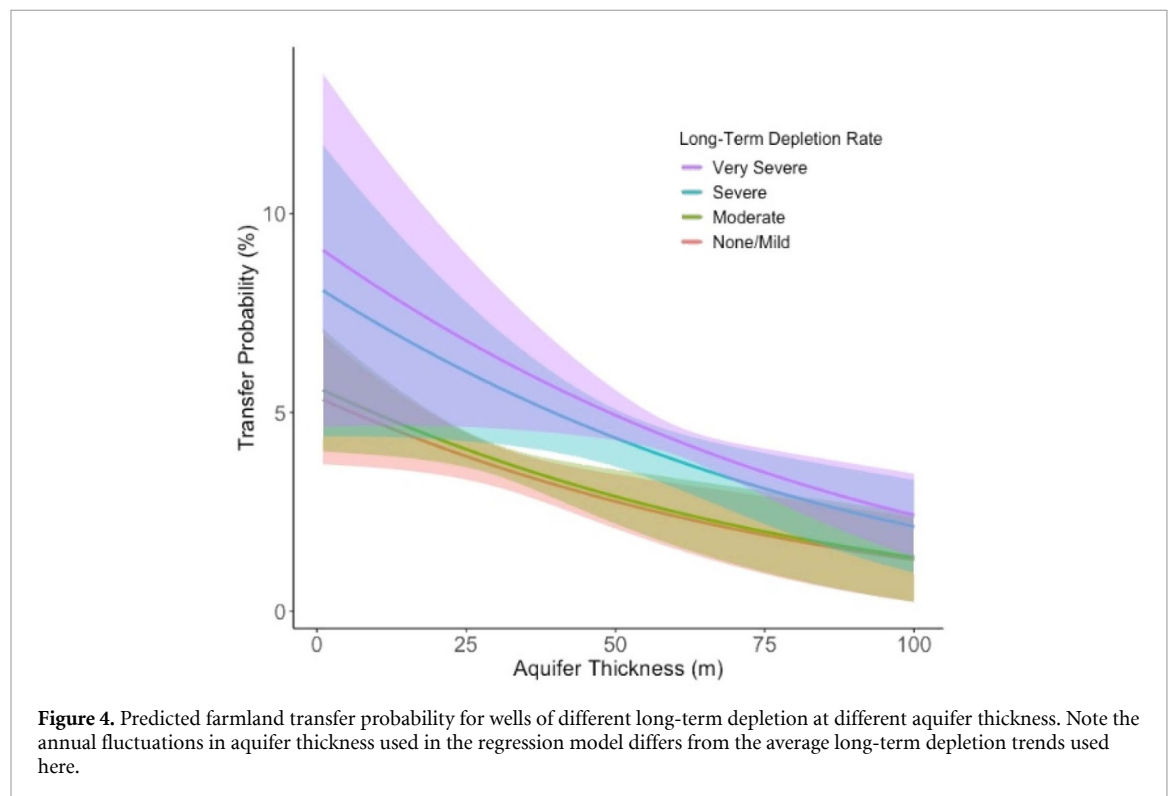


Figure 4. Predicted farmland transfer probability for wells of different long-term depletion at different aquifer thickness. Note the annual fluctuations in aquifer thickness used in the regression model differs from the average long-term depletion trends used here.

year increases the probability the irrigated parcel is transferred to another owner/operator by 0.053 percentage points. The results of the correlated RE model are presented in table 2 for the marginal effects of the aquifer thickness and depletion rate when all other variables are evaluated at their average.

While the current aquifer thickness increases the probability that an irrigated parcel will be transferred to another operator ($p < 0.001$), year-to-year fluctuations in the rate of change in aquifer thickness do not affect the probability a parcel is transferred (table 2). However, the current aquifer thickness is

related to the long-term depletion trend and these two factors act together to change the probability a parcel is transferred. Irrigated parcels with very severe rates of groundwater depletion (average >1.0 m yr⁻¹ between 1993 and 2014) are 18.7% (0.67 percentage points) more likely to be transferred than those experiencing little to no change in groundwater depletion (<0.1 m yr⁻¹) on average (figure 4). When aquifer thickness is between 25 and 75 m, the transfer probability is notably higher for wells experiencing very severe depletion rates than wells with little or no change in long-term depletion, even after considering

the 95% CI. However, at thinner (<25 m) and thicker (>75 m) aquifer thickness the impact of the long-term depletion rate on transfer probability is not as clear. Regardless of the rate of groundwater depletion, larger operators (10% larger, on average; by equation (4)) are more likely to acquire the irrigated cropland being transferred. In this way, increasing groundwater exploitation can serve as a catalyst in the widespread trend of cropland consolidation.

4. Discussion and conclusion

Groundwater depletion and the consolidation of irrigated cropland into larger farms are contemporaneous trends impacting the environmental and socioeconomic sustainability of rural areas. This study demonstrates the connection between farm consolidation/expansion and groundwater depletion. The direct effect of increasing a farm's irrigated cropland is a decrease in groundwater withdrawals (all else equal), suggesting an improvement in groundwater irrigation efficiency. A key pathway toward irrigation efficiency improvement is through better management practices, such as irrigation scheduling, use of soil moisture sensors, residue management, and proper tillage. Though irrigators apply groundwater more efficiently as they increase their irrigated cropland holdings (all else being equal), their switch from traditional center pivot to drop nozzle center pivot systems increases the depth of groundwater irrigation applications. Increasing groundwater pumping leads to loss of aquifer thickness, which in turn increases the likelihood the overlying cropland is transferred, typically to larger farm holdings (10% on average, per calculation of equation (4)). In this way, the cycle of groundwater depletion and the consolidation of irrigated cropland is amplified.

Increasing rates of groundwater depletion can accelerate a shift of irrigated cropland to larger farm holdings, which often comes at the expense of smaller farms. The USDA's Farm Service Agency offers loans to assist new small producers purchase farms, especially historically underserved and women producers (National Agricultural Statistics Service 2017). Over the course of a typical 20 year farm loan, farms experiencing very severe depletion rates ($>1.0 \text{ m yr}^{-1}$) are 12% more likely to sell their irrigated cropland than those with little to no change in depletion ($<0.1 \text{ m yr}^{-1}$). For each one-meter decline in groundwater levels, the overlying irrigated cropland loses between $\$27.7 \text{ ha}^{-1}$ and $\$128.6 \text{ ha}^{-1}$ in value (Sampson *et al* 2019). During a 20 year loan period, the loss in land value due to a 1 m yr^{-1} drop of the water table amounts to between $\$554.6$ and $\$2571.6$ decrease in land value per hectare at average conditions. For comparison, the average land price per irrigated hectare is $\$6948.1$ (Sampson *et al* 2019). Declines in aquifer thickness impact parcel prices

more for thinner aquifer segments than for thicker segments of the aquifer (Sampson *et al* 2019). If groundwater levels drop such that the cropland can no longer be irrigated, these highly leveraged producers will lose, on average, one-third of their land value (Sampson *et al* 2019). Further, the inability to irrigate can lower profitability, which greatly inhibits borrowers' ability to repay their loan. In this way, groundwater depletion is not only a matter of environmental sustainability but also of socio-economic sustainability.

The consolidation of cropland and groundwater depletion have been persistent and significant over the last several decades, with no signs of slowing. This study shows how these trends of land and groundwater resources are interconnected, which has implications for the management of these resources and the policies that shape them. Our results support previous studies (e.g. Ellis *et al* 1985, Huffaker and Whittlesey 1995, Ward and Pulido-Velazquez 2008, Pfeiffer *et al* 2010, Contor and Taylor 2013, Pfeiffer and Lin 2014, Grafton *et al* 2018, Sears *et al* 2018) that show that more efficient irrigation technologies can increase irrigation. Our findings call into question incentive-based water conservation programs that subsidize irrigation technologies, like the Environmental Quality Incentive Program and Irrigation Water Conservation Fund established in Kansas to fund the adoption of more efficient irrigation technologies since more efficient irrigation technology may not necessarily reduce groundwater withdrawals and may be disproportionately utilized by growing farms. Having demonstrated the connection between farm structure and the state of the underlying aquifer, it is important that any policy or regulation (such as formal groundwater management (Edwards 2016), proposed groundwater pumping restrictions (Cody *et al* 2015, Drysdale and Hendricks 2018), or retirements (Big Bend Groundwater Management District No. 5 Board of Directors 2019)) consider how these interventions will impact both farm structure and groundwater resources so to mitigate incidental impacts.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Conflict of interest

The authors declare no competing interests.

Author contributions

L T M, Y Z A, and N P H designed the study. Y Z A conducted the research. Y Z A, L T M, and N P H analyzed and interpreted the results. L T M, Y Z A, and N P H wrote the paper.

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