

When the well runs slow: How declining well yields and pumping interference reshape irrigation
in the High Plains Aquifer

by

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B.Sc., Lahore University of Management Sciences, Pakistan, 2013

M.S., Kansas State University, USA, 2016

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2025

Abstract

Groundwater is a critical resource for agricultural resilience against climate change and surface water variability, yet depletion poses significant risks to irrigation sustainability and food security. A key concern is declining well yields—the rate at which water can be extracted—which constrain farmers' ability to meet crop water demand at critical stages of growth. While prior studies recognize the importance of well yields in irrigation decisions, empirical evidence on their impact remains scarce. Additionally, economic analyses of pumping externalities overlook well interference spillover effects despite their hydrological and economic significance.

This study address three key gaps in the literature: (1) estimating well yields and analyzing their spatial and temporal variation across the High Plains Aquifer region of Kansas, (2) evaluating farmers' irrigation response to limited well yields along extensive (irrigated acreage), indirect intensive (crop choice), and direct intensive (water application depth) margins, and (3) estimating well yield spillover effects and analyzing how these affect water use. Using a 24-year panel dataset of over 6000 wells, we find substantial well yield declines (up to 33%) in high depletion districts, driven by reduced saturated thickness. Econometric analysis reveals that a 100 GPM decrease in well yield decreases irrigated area by 13.5 acres, water application depth by 0.47 inches and the probability of planting corn by 3 percentage points. Water use adjustments are most responsive at low to moderate well yields (250-750 GPM), with three quarters of adjustment in water use occurring at the extensive margin.

Furthermore, well interference generates spillover effects on the neighboring farmers, with median well yield reductions ranging from 6% in low transmissivity areas to 20% in high transmissivity areas. High well density (10 neighbors) can reduce water use by 22.3% compared to isolated wells. Future groundwater governance could benefit from spatially explicit

regulations that account for hydrological constraints revealed by well interference effects. Future research should explore how well yields influence efficient irrigation technology adoption, agricultural land values and market-based water trading mechanisms.

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Dedication

To my teacher, Dr. Nathan Paul Hendricks, a man of integrity, skill and a beautiful soul.
Learning from him has been a privilege.

Chapter 1 - Introduction

Agriculture relies heavily on groundwater as it provides a critical buffer against adverse impacts of climate change (Mieno et al., 2024) and surface water variability (Scanlon et al., 2023). As global irrigation demand rises due to climate change (Zhou et al., 2010; Wada et al., 2013; Wada & Bierkens, 2014; Kreins et al., 2015; Obembe et al., 2023), depleting groundwater reserves (Wada et al., 2010; Scanlon et al., 2012) pose significant risk to agricultural sustainability and long-term food security.

A key concern arising from groundwater depletion is the decline in well yields which constrain a farmer's ability to meet crop water demand during critical stages of growth (Foster et al., 2015a). While the importance of considering well yields in explaining farmers' irrigation decisions has been recognized in the literature (Foster et al., 2014; Foster et al., 2015a; Foster et al., 2015b, 2017; Hrozencik et al., 2017; Manning & Suter, 2019; Rad et al., 2020), few studies have moved beyond theoretical modelling and numerical simulation. Empirical evidence on how limited well yields affect farm-level irrigation decisions remains scarce.

This gap is particularly concerning in heavily mined aquifers with low recharge rates such as the western Kansas and northern Texas regions of High Plains Aquifer where water levels have drastically declined (Scanlon et al., 2012; McGuire, 2017). In these regions well yields are likely to change significantly over time, yet no study has systematically evaluated their spatial and temporal variation.

Furthermore, the economic literature has extensively discussed groundwater pumping externalities, typically framing them in terms of increased pumping cost due to lower aquifer levels (Gisser & Sanchez, 1980; Feinerman & Knapp, 1983; Rubio & Casino, 2001; Guilfoos et al., 2013; Guilfoos et al., 2016) or long-term depletion affecting future availability of water

(Provencher & Burt, 1993; Merrill & Guilfoos, 2018). However, a crucial third externality arising from the reduced well yield caused by pumping at neighboring wells has largely been overlooked. Early economic studies relied on simplified “single cell” or “bathtub” aquifer models assuming that pumping by one user instantly and uniformly reduces water availability for all users (Gisser & Sanchez, 1980; Feinerman & Knapp, 1983; Negri, 1989; Provencher & Burt, 1993; Burness & Brill, 2001; Rubio & Casino, 2001; Koundouri, 2004). More recent research recognizes groundwater as a spatially explicit resource, where pumping externalities dissipate with distance between wells (Saak & Peterson, 2007; Brozović et al., 2010; Pfeiffer & Lin, 2012; Guilfoos et al., 2013; Peterson & Saak, 2018; Manning & Suter, 2019). Yet even these studies fail to fully account for hydrological interactions that govern well interference.

When a well operates within the radius of influence of another, their cones of depression overlap, creating additional drawdown known as well interference (Kasenow, 2001). In the intersecting zone, the total drawdown becomes the combined effect of both wells, meaning that closer proximity leads to greater interference and lower well yields (Kasenow, 2001). This forces neighboring wells to compete for the same water, reducing individual productivity. To accurately assess the impact of pumping on neighboring wells, explicitly modelling the overlap of cones of depression is essential (Kasenow, 2001). However, despite acknowledging the spatially explicit nature of groundwater resources, recent studies have not incorporated this critical factor, leaving a key gap in understanding true economic consequences of well interference.

This study attempts to address critical research gaps identified above. The organization of this dissertation is as follows. In Chapter 2 we estimate well yields over time for groundwater wells overlaying the Kansas portion of the High Plains Aquifer while accounting for hydrological rules that govern the behavior of groundwater. Additionally, we discuss the spatial

and temporal variation in well yields across five groundwater management districts in Kansas. In Chapter 3 we provide empirical evidence of how farmers adapt to limited well yields using a 24-year panel dataset encompassing over 6000 wells in Kansas. We analyze water use adjustments at the extensive margin (irrigated acres), indirect intensive margin (crop choice) and the direct intensive margin (water application depth per acre) in the face of limited well yield. In Chapter 4 we estimate the well yield spillover effects and discuss how these translate into change in water use at farm level. In Chapter 5 we provide concluding remarks.

An important limitation of our study is that we do not quantify the potential strategic behavior between the neighboring farmers wherein neighbors' extraction reduces the value of saving water for future use. This could incentivize individual farmers to increase their current period pumping in order to secure a larger share of the resource, as suggested by Pfeiffer and Lin (2012).

Chapter 2 – Estimation of well yields

2.1 Introduction

There is a widespread agreement among water resource economists that ignoring hydrological rules that govern the behavior of groundwater may lead to misrepresentation of farmers' irrigation decisions (Saak & Peterson, 2007; Brozović et al., 2010; Pfeiffer & Lin, 2012; Guilfoos et al., 2013; Foster et al., 2014; Foster et al., 2015a; Foster et al., 2015b, 2017; Hrozencik et al., 2017; Peterson & Saak, 2018; Manning & Suter, 2019; Rad et al., 2020). Well yield is the most popular among recently acknowledged parameters. It refers to the maximum gallons per minute that can be obtained from a given well (Kasenow, 2001). In the case of a heavily mined aquifer with low recharge rates such as the western Kansas and northern Texas regions of the High Plains Aquifer where water levels have drastically declined (Scanlon et al., 2012; McGuire, 2017), it is highly likely to observe significant changes in well yield over time. Similarly, pumping by one farmer reduces the water table of neighboring farmers thereby increasing their pumping cost and decreasing their future availability of water. This phenomenon is known as well interference (Kasenow, 2001).

Well yield and interference may affect farming decisions more than just through pumping cost. Water application at different stages of growth affects the crop yield in different ways. Given abundant availability of water, farmers apply less water in early season than at later stages of growth (Peterson & Ding, 2005). And given low availability of water, farmers reduce crop acres to ensure enough water supply in the critical stages of the growing season (Rad et al., 2020). Despite important implications of well yield for irrigation decisions, no study has evaluated spatial and temporal variation in the well yields. Further, no data are available on how much reduction in a particular well's yield is caused by interference of the neighboring wells.

The objective of this chapter is to estimate yields over time for groundwater wells overlaying the Kansas portion of the High Plains Aquifer while accounting for hydrological rules that dictate the behavior of groundwater. Additionally, this study evaluates the spatial and temporal variation in well yields across five groundwater management districts in Kansas.

2.2 Basic groundwater hydrology

An aquifer is a geological formation comprised of permeable layers of rock and soil that are saturated with water. Groundwater is stored in and moves through the pores or void spaces in these geological materials. When a geological material is completely saturated with water, the porosity becomes a measure of total water stored per unit volume of that material (Todd & Mays, 2004). However, not all the water stored in an aquifer can be obtained during pumping. This is due to surface tension and attraction between molecules that keep some of the water held within the rock or soil medium (Todd & Mays, 2004). Hence the porosity of a geological material can be divided into two components namely drainable porosity (specific yield) and non-drainable porosity (specific retention).

An aquifer is confined by an impermeable layer of clay or bedrock at the bottom. The vertical distance from the water table to the bottom of the aquifer is called saturated thickness. Saturated thickness along with hydraulic conductivity defines transmissivity of the aquifer which is one of the most important determinants of well yield. The property of geological materials to transmit or conduct water is called hydraulic conductivity. Formally, hydraulic conductivity of a material can be defined as the distance per unit time the water can traverse through a unit cube of that material under the influence of hydraulic gradient (Kasenow, 2001). Transmissivity of the aquifer can be obtained by multiplying hydraulic conductivity with the complete aquifer thickness (Kasenow, 2001):

$$Transmissivity = \text{hydraulic conductivity} \times \text{saturated thickness} \quad (2.1)$$

Simply put, hydraulic conductivity represents the conductivity of a particular material under hydraulic gradient and transmissivity is the hydraulic conductivity of the aquifer. Note that in this study the unit of measurement for saturated thickness is feet (ft), for hydraulic conductivity it is feet per day (ft/day) and for transmissivity it is square feet per day (ft^2/day). Specific yield is dimensionless and it is expressed as a ratio (0 to 1).

During pumping, the water table in a well declines from its initial static level. This drop in the water level is known as drawdown. In his seminal work, Theis (1935) proposed a method to estimate the drawdown (s_a) in the aquifer with given specific yield (S) and transmissivity (T) due to pumping in own well located at the distance (r) from an observation well and discharging water at rate (Q) for given number of days (t):

$$s_a = \frac{Q}{4\pi T} \int_{\frac{r^2 S}{4Tt}}^{\infty} \left(\frac{e^{-\mu}}{\mu} \right) d\mu \quad (2.2)$$

or

$$s_a = \frac{Q}{4\pi T} \left[-0.5772 - \ln(\mu) + \mu - \frac{\mu^2}{2 * 2!} + \frac{\mu^3}{3 * 3!} - \frac{\mu^4}{4 * 4!} + \dots \right] \quad (2.3)$$

where μ is the Boltzmann variable of integration and its value can be calculated as:

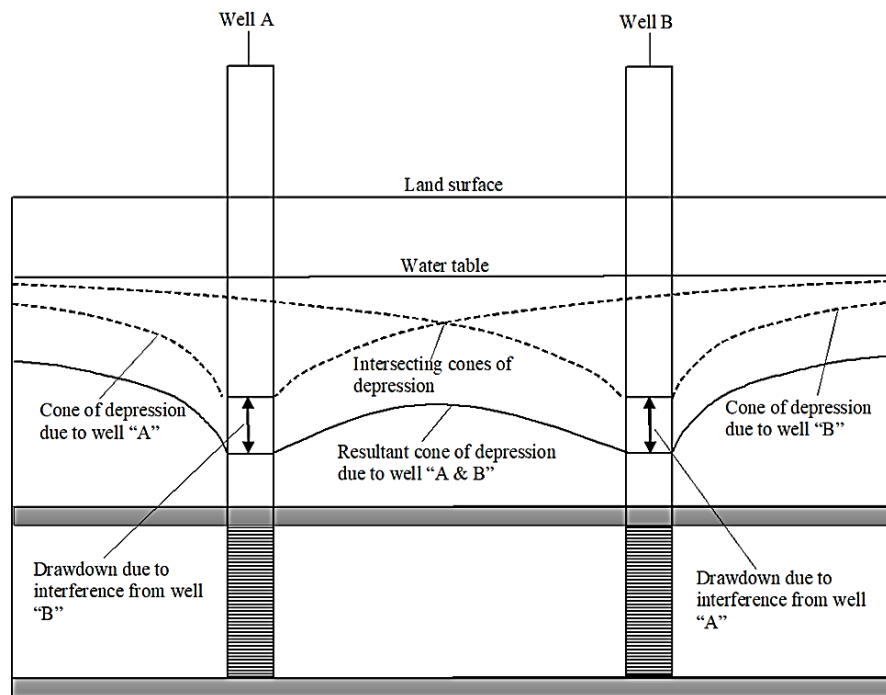
$$\mu = \frac{r^2 S}{4Tt} \quad (2.4)$$

Based on (Hecox et al., 2002), we approximate the infinite series presented in (2.3) up to the fifth power of μ and denote it as Theis well function $W(\mu)$ so that the drawdown (s_a) can be written as:

$$s_a = \frac{Q}{4\pi T} W(\mu). \quad (2.5)$$

If a groundwater well has another well operating within its radius of influence, then intersecting cones of depression produce additional drawdown known as well interference drawdown (Kasenow, 2001). The actual drawdown in the area of intersection is the sum of drawdowns from each well. Hence, the closer two wells are located, the larger the well interference and the smaller the yield for each well (Kasenow, 2001). Figure 2.1 illustrates interference between two wells operating simultaneously in an aquifer. The dashed curves represent individual cones of depression produced by each well. And the solid curve represents the resultant cone of depression due to interference. Note that the resultant curve lies beneath the individual cones of depression.

Figure 2.1. Illustration of interference between two wells operating simultaneously



Source: Redrawn based on Kasenow (2001)

The drawdown in own well due to interference with the neighboring well (s_n) for a given distance between wells (r_n), pumping days of neighboring well (t_n) and a discharge rate (Q_n) is given as:

$$s_n = \frac{Q_n}{4\pi T} W(\mu_n), \quad (2.6)$$

where

$$\mu_n = \frac{r_n^2 S}{4T t_n} \quad (2.7)$$

It is important to note that interference between wells is the main source of externality during the pumping season. When two wells operate together, they reduce available saturated thickness for each other by causing extra drawdown in neighboring well. This results in reduced transmissivity and lower well yields.

2.3 A review of hydrologic reports by Kansas state agencies

In this section we provide a brief overview of methods adopted by Kansas state agencies including Kansas Geological Survey (KGS) and the Kansas Department of Agriculture – Division of Water Resources (DWR) to estimate well yields.

2.3.1 Minimum saturated thickness calculation

Hecox et al. (2002) employed the Theis (1935) equation for determining the minimum saturated thickness required to maintain a specific pumping rate and duration. To assess the influence of adjacent irrigation wells, a hypothetical scenario was considered, incorporating four wells operating at the same pumping rate each positioned at a distance of half mile from the primary well.

2.3.2 Well yield calculation

Liu et al. (2012) used a simplified approximation of the Theis (1935) equation to estimate the maximum potential well yield for each one square mile section within Groundwater Management District 3. This calculation assumed a single representative well per cell, neglecting interference effects from neighboring wells. These potential well yields did not account for practical factors affecting actual well yields such as pump specification, screen intervals or well interference resulting in overestimated values. To address these practical limitations, a three-step adjustment procedure was implemented by Liu et al. (2012):

Step-1: Pumping rates from field inspections were spatially interpolated, defining them as observed well yields.

Step-2: An adjustment ratio was computed by dividing observed well yields by potential well yields for each model cell.

Step-3: Practical well yields were determined by multiplying the adjustment ratio by the potential well yield.

2.3.3 Haskell County court case concerning a claim of water right impairment

The Kansas Water Appropriation Act of 1945 enforces the principle of prior appropriation (first in time, first in right), granting senior water rights precedence over junior water rights. If senior rights are impaired, junior rights holders may be mandated to curtail or cease water extraction.

In May 2012, Garetson Brothers, an agricultural operation in Haskell County, initiated legal proceedings in the District Court, contending that the neighboring junior water rights were impairing their senior water right. The court appointed the Kansas Department of Agriculture's Division of Water Resources (DWR) as the investigating authority.

The DWR deployed monitoring equipment to assess the claim of water right impairment. Pumping tests conducted in 2013 measured drawdown, pumping rates, and durations at both the target and neighboring wells. Aquifer properties were derived using AQTESOLV software and subsequently applied in the Theis equation to model drawdown effects. While this approach provides the highest level of accuracy, its reliance on continuous real-time monitoring of water levels and pumping rates renders it impractical for large scale regional assessment of well yields and interference.

2.4 Estimation of well yields

In practice, well yields are determined in a field test generally conducted at the time of well construction. During a field test, the well is operated for regular intervals and resultant drawdown and recovery in the water table is measured. These measurements are then used to determine well yield and aquifer properties such as transmissivity and storativity. These field tests are expensive and time consuming, so they are rarely conducted on regular intervals. Therefore, time series data on well yields are not available in public records.

Water well completion records (WWC5) in the state of Kansas are pivotal in calculation and calibration of well yields in this study. Kansas Geological Survey (KGS) maintains these records that contain crucial well and aquifer characteristics including well yields estimated at the time of construction, well depth, depth to static water level, length of casing and screen and detailed lithology of geological formations surrounding the well bore.

Saturated thickness at the time of well construction was calculated as the vertical distance between static water table and the depth of well specified in the WWC5 database. Additionally, a time series of saturated thickness was obtained based on PLSS section level water table elevation dataset obtained from KGS. This data set provides elevation of land surface, water table and

bedrock. The vertical distance between the water table and bedrock was calculated as section level saturated thickness. PLSS section level data on aquifer parameters namely hydraulic conductivity (K) and specific yield (S) were obtained from KGS. These data were then merged with relevant points of diversion located within each section.

2.4.4 Estimation of well yields without neighbors

Well yields without neighbors were calculated by solving equation (2.5) for Q so that the drawdown s_a equals one-third of available aquifer thickness (Liu et al., 2012). We assume that aquifer parameters K and S remain constant over time. So, the temporal variation in well yields stems from the changes in saturated thickness.

2.4.5 Estimation of well yields with neighbors

In the case of well interference the total drawdown (s_t) in a given well can be calculated as the sum of drawdown from own pumping in the target well (s_a) and that from pumping in the neighboring wells (s_n):

$$s_t = s_a + s_n \quad (2.8)$$

For calculation of well yields with neighbors we solve equations (2.5) and (2.6) for maximum obtainable discharge rate when total drawdown equals one third of saturated thickness (Liu et al., 2012). As provided in Kansas Administrative Regulation § 5-21-3¹, which governs well spacing requirements, any new well drilled into the Ogallala Aquifer must maintain a minimum distance of 2,640 feet (0.5 miles) from existing wells. Consistent with this regulation, Hecox et al. (2002) assume a distance of 0.5 miles between neighboring wells. To account for potential interference from wells located beyond this minimum spacing threshold, we created an

¹ <https://www.law.cornell.edu/regulations/kansas/K-A-R-5-21-3>

additional buffer of 0.25 miles around each existing well. Consequently, our analysis considers all wells located within 0.75 mile radius of a given target well while conservatively assuming that these neighboring wells were positioned at the regulated minimum distance of 0.5 miles. Based on Liu et al. (2012), we assume the pumping season lasts for 90 days.

2.4.6 Python-based optimization for estimation of well yields

We used Pyomo, a Python-based optimization modelling language to maximize total pumping rates from wells while respecting constraints on drawdown. The Python code provided in Appendix A optimizes pumping rates while accounting for local drawdown (due to own pumping in the target well) and well interference (additional drawdown caused by neighboring wells). It begins by installing necessary libraries and loading well level hydrological data from CSV files.

The objective function maximizes the total pumping rates across all wells expressed as $\sum(\text{model.pump}[g] \text{ for } g \text{ in the batch_groups})$. The drawdown is calculated using equations 2.5 and 2.6. Key variables include:

`model.pump[g]`: Pumping rate (decision variable)

`model.saqu[g]`: Drawdown due to own pumping in the target well

`model.sneighbor[g,i]`: Drawdown due to well interference

`model.sall[g]`: Total drawdown (sum of drawdown due own pumping and interference)

The primary constraint ensures total drawdown (`sall`) never exceeds one-third of the saturated thickness for each well. Due to the problem's large scale the code processes wells in batches of 100 groups for computational efficiency. We used IPOPT solver for nonlinear optimization. This solver iteratively adjusts pumping rates to maximize extraction while

respecting the drawdown constraints. Finally, the optimized pumping rates are exported to an excel file for analysis.

2.4.7 Calibration of well yields

The well yields discussed in sections 2.3.1 and 2.3.2 are based on the assumption that the entire saturated thickness is screened. Additionally, practical factors affecting yields such as pump type and screen intervals are not taken into account (Liu et al., 2012). Therefore, calculated yields are only potential yields and are expected to be larger than actual. In order to take practical factors affecting yields in the field conditions, an adjustment ratio was calculated to convert potential well yields into practical well yields following the method used by Liu et al. (2012). This ratio was calculated by dividing well yields reported in drillers' logs at the time of well construction by potential yields calculated using saturated thickness at the time of well construction. Practical yields were calculated by multiplying the adjustment ratio with potential yields for all future years and the adjustment ratio was assumed to remain constant over time as shown in the following equations for well i :

$$Adjustment\ ratio_i = \frac{Observed\ well\ yield\ at\ time\ of\ well\ construction_i}{Potential\ well\ yield\ at\ the\ time\ of\ well\ construction_i}, \quad (2.9)$$

$$Practical\ well\ yield_{it} = Adjustment\ ratio_i \times Potential\ well\ yield_{it}. \quad (2.10)$$

The adjustment ratio has an average value of 0.71 and a standard deviation of 0.63. The middle 50% of the values lie between 0.24 and 0.98.

2.4.8 Summary of well yield estimation method

In this section we provide a step-by-step summary of the method used to calculate and calibrate well yields.

Step-1: Observed well yields from pumping tests conducted at the time of well construction were retrieved from Water Well Completion Records (WWC5) Database.² Additionally, aquifer characteristics at the PLSS section level – including hydraulic conductivity (K), specific yield (S) and time series saturated thickness values – were obtained from KGS.³ These datasets were merged with point of diversion locations within each PLSS section from the WIMAS database⁴ from KGS to obtain well-level hydrological data.

Step-2: Potential well yields were estimated using non-linear optimization, incorporating the well-level hydrological data obtained in Step 1. The calculation determined the maximum feasible discharge rate while accounting for local drawdown (due to pumping in the target well (equation 2.5)) and well interference (equation 2.6). Well interference represents the additional drawdown introduced by neighboring wells assumed to be operating at the equivalent pumping rate following Hecox et al. (2002).

Step-3: Following Liu et al. (2012), an adjustment ratio was computed by dividing the well yields documented in drillers' logs (recorded at the time of well construction) by potential well yields calculated using saturated thickness at the time of well construction using steps 1 and 2. This ratio served as the calibration factor to reconcile potential well yield estimates with observed field data.

Step-4: Practical well yields were computed by multiplying the adjustment ratio from Step 3 times the potential well yield from Step 2. This calibration adjustment ensured that practical well yields reflect actual operational conditions.

² <https://www.kgs.ku.edu/Magellan/WaterWell/index.html>

³ Obtained through personal communication with Kansas Geological Survey.

⁴ https://geohydro.kgs.ku.edu/geohydro/wimas/query_setup.cfm

2.4.9 Limitations of the well yield estimation methodology

Our well yield estimation methodology is subject to certain limitations. First, we assume a 90-day operational period for all wells during a pumping season as outlined in (Liu et al., 2012), and further assume simultaneous operation of all wells within a given neighborhood. In practice, however, pumping schedules may vary among wells in the same vicinity. Additionally, following Hecox et al. (2002), we assume identical pumping rates for both primary well and the neighboring wells, though actual conditions may involve rate disparities.

A methodological refinement in our study involves using actual number of neighboring wells. While Hecox et al. (2002) assume four neighboring wells each located at 0.5 mile distance from the target well, our analysis calculates actual neighboring wells within 0.75 mile radius – the median radius of influence across all wells in our dataset.

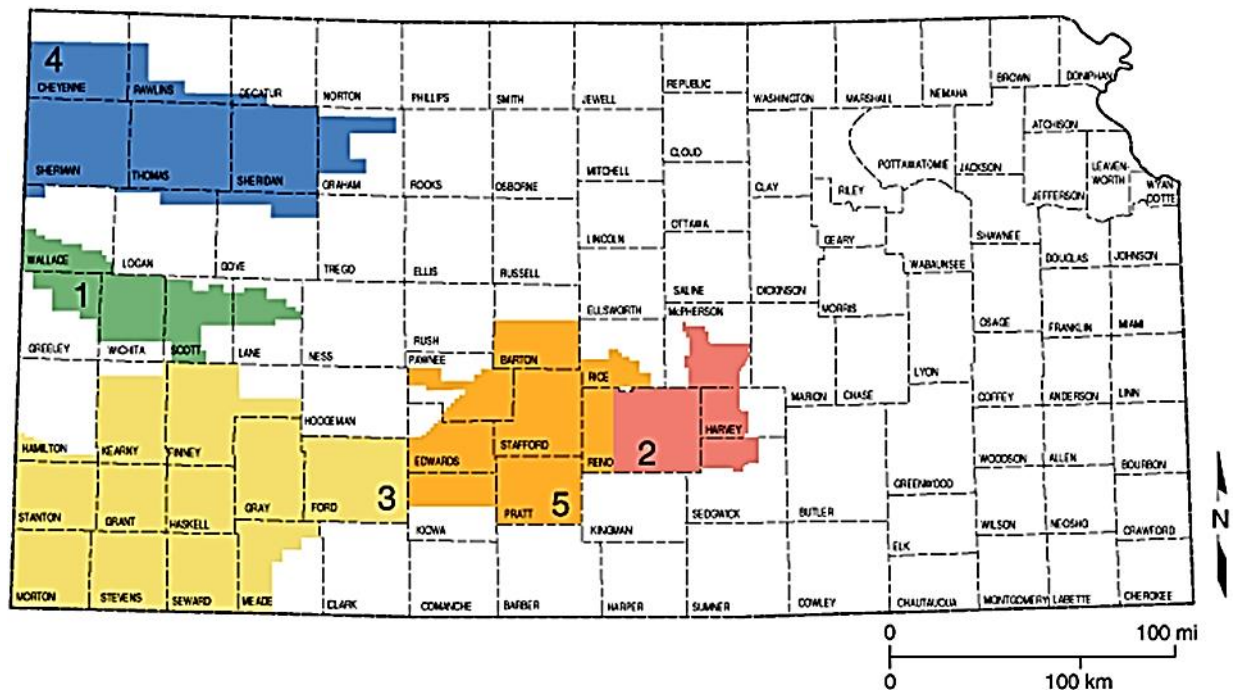
Furthermore, we do not account for strategic pumping behavior of neighboring farmers. In regions with significant well interference, farmers may initiate pumping earlier to secure groundwater access before neighboring extraction begins. Our model also does not account for behavioral adjustments by farmers operating multiple wells who may seek to minimize interference from own wells.

2.5 Spatial and temporal variation in well yields

The Kansas portion of the High Plains Aquifer has been divided into five local units called groundwater management districts (GWMDs) for administrative and planning purposes (Figure 2.2). Figure 2.3 presents a time series plot of the average well yield with neighbors from 1991 to 2014 across five GWMDs. All GWMDs exhibit a declining trend in well yield over time indicating a general drop in groundwater availability. The decline is particularly noticeable in GWMDs 1, 3 and 4. In GWMD-1 average well yield decreased from 444 GPM in 1991 to 298

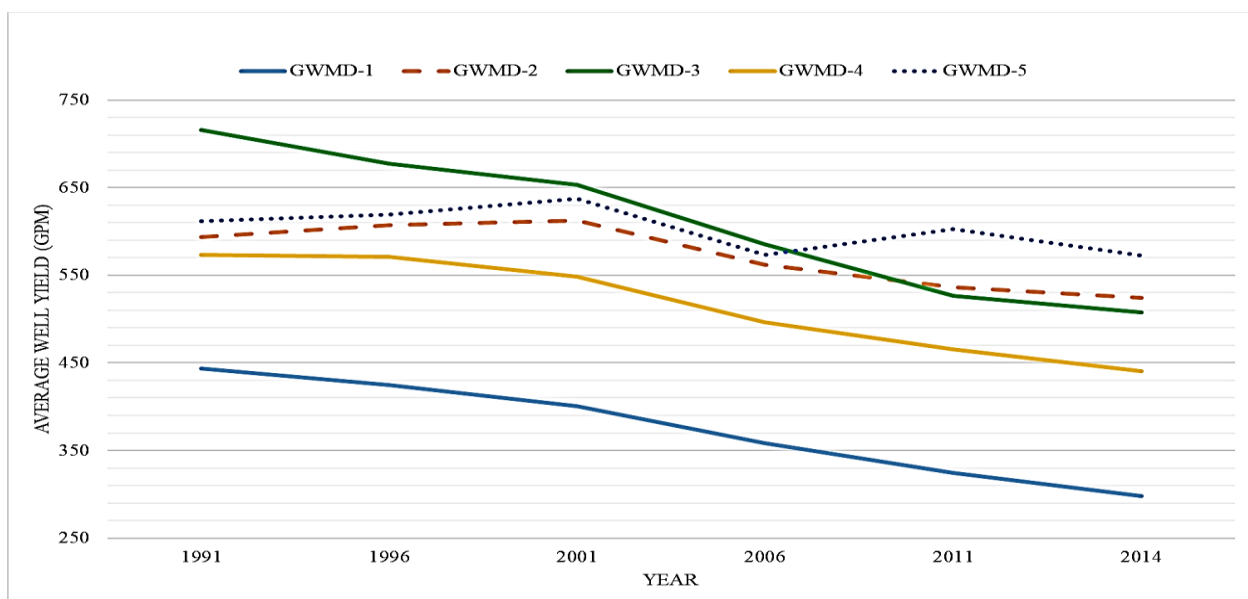
GPM in 2014, indicating a 33% decline. In GWMD-3 the average well yield decreased from 716 GPM in 1991 to 508 GPM in 2014, marking a 29% decline. Similarly, in GWMD-4 average yield decreased from 573 GPM in 1991 to 441 GPM in 2014, indicating a 23% decline. GWMD-1 and GWMD-4 had consistently lower average well yields compared to other districts. GWMD-2 and GWMD-5 exhibited relative stability in average well yields.

Figure 2.2. Map of groundwater management districts (GWMDs) in Kansas



Source: Kansas Geological Survey (<https://www.kgs.ku.edu/Hydro/gmd.html>)

Figure 2.3. Trend in average well yields overtime and across GWMDs



Chapter 3 – How farmers adapt to declining well yields: empirical evidence from the High Plains Aquifer

3.1 Introduction

Agriculture heavily relies on groundwater as it provides critical buffer against adverse impacts of climate change (Mieno et al., 2024) and surface water variability (Scanlon et al., 2023). As global irrigation demand rises due to climate change (Zhou et al., 2010; Wada et al., 2013; Wada and Bierkens, 2014; Kreins et al., 2015), depleting groundwater reserves (Wada et al., 2010; Scanlon et al., 2012) pose significant risk to agricultural sustainability and long-term food security.

A key concern arising from groundwater depletion is the decline in well yields which constrain a farmer's ability to meet crop water demand during critical stages of growth (Foster et al., 2015). While the importance of considering well yields in explaining farmers' irrigation decisions has been recognized in the literature (Foster et al., 2014, 2015, 2017; Hrozencik et al., 2017; Manning and Suter, 2019; Rad et al., 2020), few studies have moved beyond theoretical modelling and numerical simulation. Empirical evidence on how limited well yields affect farm-level irrigation decisions remains scarce.

In this paper, we provide empirical evidence on how farmers adapt to limited well yields using a 24-year panel dataset encompassing over 6000 wells overlaying the Kansas portion of the High Plains Aquifer. We analyze water use adjustments at the extensive margin (irrigated area), indirect intensive margin (crop choice) and direct intensive margin (water application depth per acre) in the face of limited well yield.

3.2 Conceptual model

For a given growing season, a farmer's irrigation demand can be decomposed into three decisions: (i) the number of acres to irrigate (ii) the selection of crops to plant, and (iii) the soil moisture target. These decisions are subject to expected weather and water supply constraints. Well yield is the maximum water extraction rate for a given well and, therefore, constrains a farmer's ability to deliver required soil moisture at critical stages of crop growth. With higher well yield, the farmer can meet intra-season crop water demand at desired times for any weather conditions. Conversely, a lower well yield reduces the farmer's ability to meet moisture requirements during critical stages of plant growth, particularly in dry weather, resulting in lower crop yield and profitability (Rad et al., 2020). Let the per acre profit from crop j be:

$$\pi_j(W_j, y) = p_j Y_j(W_j, y) - c(W_j), \quad (3.1)$$

where W_j is the seasonal water application per acre for crop j , y is the well yield, p_j is crop's output price and $Y_j(W_j, y)$ is the expected harvested yield of crop j . The reason for y explicitly entering $Y_j(\cdot)$ is that, if y is low, the farmer may not be able to meet intra-season soil moisture requirements during critical growth stages. Hence for the same W_j , a lower y reduces achievable crop yield due to sub-optimal irrigation scheduling (Foster & Brozović, 2018; Rad et al., 2020).

$c(W_j)$ denotes the pumping cost of water per acre. If the farmer dedicates S_j proportion of irrigated acres A to crop j the total expected profit from those acres is $AS_j[p_j Y_j(W_j, y) - c(W_j)]$. Summing over all crops j gives total profit from the irrigated acreage as

$A \sum_{j=1}^J S_j [p_j Y_j(W_j, y) - c(W_j)]$. Additionally, the groundwater right associated with a given well restricts the maximum number of irrigated acres to $\bar{A}$ and maximum amount of groundwater pumped to $\bar{W}$. The farmer's constrained profit maximization problem is

$$\max_{A, \{S_j\}, \{W_j\}} A \sum_{j=1}^J S_j [p_j Y_j(W_j, y) - c(W_j)] \quad (3.2)$$

$$\text{s. t.} \quad A \leq \bar{A}$$

$$A \sum_{j=1}^J S_j W_j \leq \bar{W}$$

$$\sum_{j=1}^J S_j = 1, \quad S_j \geq 0 \quad \forall j,$$

$$A \geq 0, W_j \geq 0 \quad \forall j$$

The Lagrangian of the constrained profit maximization problem is as follows:

$$\mathcal{L} = A \sum_{j=1}^J S_j [p_j Y_j(W_j, y) - c(W_j)] + \lambda_1 (\bar{A} - A) + \lambda_2 \left(\bar{W} - A \sum_{j=1}^J S_j W_j \right) + \lambda_3 \left(1 - \sum_{j=1}^J S_j \right) \quad (3.3)$$

where $\lambda_1 \geq 0$ is the shadow price of adding an irrigated acre, $\lambda_2 \geq 0$ is the shadow price of adding a unit of water, and $\lambda_3 \geq 0$ is the multiplier associated with crop share equality constraint. The first-order conditions for crops with positive share ($S_j > 0$) and positive water application ($W_j > 0$), are as follows:

$$\frac{\partial \mathcal{L}}{\partial A} = \sum_{j=1}^J S_j [p_j Y_j(W_j, y) - c(W_j)] - \lambda_1 - \lambda_2 \sum_{j=1}^J S_j W_j = 0 \rightarrow \sum_{j=1}^J S_j \pi_j(W_j, y) = \lambda_1 + \lambda_2 \sum_{j=1}^J S_j W_j \quad (3.4)$$

$$\frac{\partial \mathcal{L}}{\partial S_j} = A [p_j Y_j(W_j, y) - c(W_j)] - A \lambda_2 W_j - \lambda_3 = 0 \rightarrow \pi_j(W_j, y) - \lambda_2 W_j = \frac{\lambda_3}{A} \quad \forall j \quad (3.5)$$

$$\frac{\partial \mathcal{L}}{\partial W_j} = A S_j \left[p_j \frac{\partial Y_j(W_j, y)}{\partial W_j} - \frac{\partial c(W_j)}{\partial W_j} \right] - \lambda_2 A S_j = 0 \rightarrow \frac{\partial \pi_j(W_j, y)}{\partial W_j} = \lambda_2 \quad \forall j \quad (3.6)$$

the complementary slackness implies:

$$\lambda_1 (\bar{A} - A) = 0: \text{ if } A < \bar{A} \text{ then } \lambda_1 = 0, \text{ conversely, if } \lambda_1 > 0 \text{ then } A = \bar{A}$$

$\lambda_2(\bar{W} - A \sum_{j=1}^J S_j W_j) = 0$: if $A \sum_{j=1}^J S_j W_j < \bar{W}$ then $\lambda_2 = 0$, conversely, if $\lambda_2 > 0$ then $\bar{W} = A \sum_{j=1}^J S_j W_j$.

Equation (3.4) implies that profit per acre across the chosen crop mix from one additional irrigated acre equals the sum of shadow price of land constraint (λ_1) and shadow value of extra water used on additional acre ($\lambda_2 \sum_{j=1}^J S_j W_j$). The second first-order condition implies that for a given seasonal per acre water application (W_j), only the crop with highest per acre profit is chosen. If multiple crops have the same profit, they can co-exist in positive shares. The third first-order condition states that for every crop that is irrigated, per acre marginal profit of water equals the shadow price λ_2 of the water availability constraint. If the water constraint is binding, $\lambda_2 > 0$ and if it is not binding, the farmer applies water to the point where marginal profit is zero.

The farmers may respond to a change in well yield in three different ways: changing irrigated acres, changing crops, or changing the water application depth.

3.2.1 Irrigated acreage response

With a large well yield, the farmer can meet crop water demand across all irrigated acres simultaneously. This reduces risk of water stress at peak evapotranspiration stages. Therefore, the farmer expands irrigated acres to the point where either the land or water availability constraints bind or the well yield can no longer guarantee the profit maximizing seasonal water application for all acres.

Suppose a crop j yields highest profit per acre when sufficiently irrigated i.e. profit per acre $\pi_j(W_j, y)$ is maximized at a certain level of seasonal water application per acre W_j . The farmer may not be able to irrigate all potential acres $\bar{A}$ at level W_j due to either (i) total water extraction constraint $\bar{W}$ or (ii) lower well yield. Therefore, to avoid yield loss across larger

acreage, the farmer may concentrate irrigation on fewer acres, thus ensuring enough soil moisture when needed.

3.2.2 Crop choice response

Well yield constrains the farmer's ability to deliver sufficient soil moisture at critical stages of crop growth thus affecting crop yields. Therefore, with lower well yield, the profitability of water-intensive crops might become lower than that of less water intensive crops that can better tolerate limited or less-frequent irrigation. Therefore, for a given W , a profit maximizing farmer may choose less water-intensive crops if lower well yield significantly reduces yield of water intensive crops.

3.2.3 Water application depth response

The well yield dictates how quickly a given amount of water can be delivered during the growing season. The crop yield not only depends on the seasonal water application per acre W_j but also “when” this water is applied. With a low well yield, the farmer cannot apply high volumes of water quickly which may lead to water stress during critical stages of growth even though seasonal water application is sufficient. If the well yield is so low that sufficient water cannot be applied when needed, additional increments of W_j might not translate into higher yield gains. Therefore, the farmers may choose lower optimal W_j or the farmer may reduce irrigated acres to concentrate water application over a smaller area. Conversely, with higher well yield, a farmer can meet intra-season crop water demand reliably. In such a scenario, the farmer increases W_j to the point where marginal revenue equals marginal cost, as long as the annual constraint is not binding.

In summary, there exists a range of well yields that are sufficiently large to satisfy crops' irrigation scheduling needs. In this range, a slight decrease in well yields does not result in a

sharp decline in crop yields as water deficit at critical stages of crop growth is minimal or non-existent. Therefore, the farmer can adjust seasonal water application depth in response to slight changes in well yield and does not switch crops or reduce irrigated acreage. Conversely, there exists a range of well yields in which crops' irrigation scheduling needs cannot be met. A further decrease in well yield results in sharp decline in crop yields due to severe water deficit at peak evapotranspiration stages. In this case the farmer responds by switching to less water intensive crops or concentrating available water to fewer irrigated acres (Foster et al., 2014; Rad et al., 2020).

3.2.4 Decomposition of elasticity of water use with respect to well yield

Empirically, we decompose the change in water use with respect to well yield into extensive and intensive irrigation margin effects in the spirit of Hendricks and Peterson (2012) and Lee and Hendricks (2022). The optimal solution $\{A^*(y), S_j^*(y), W_j^*(y)\}$ to the farmer's profit maximization problem above can be characterized as a function of well yield. Where $A^*(y)$ denotes optimal irrigated acreage, $W_j^*(y)$ denotes the optimal water application per acre (acre-inches per acre) for each of the possible $j = 1, \dots, J$ crop choices, and $S_j^*(y)$ denotes the optimal proportion of irrigated acreage planted to crop j . The average water application per acre is $\sum_{j=1}^J S_j^*(y)W_j^*(y)$. The total optimal water use can be obtained by multiplying irrigated acreage by average water application per acre:

$$\tilde{W}^*(y) = A^*(y) \sum_{j=1}^J S_j^*(y)W_j^*(y). \quad (3.7)$$

Differentiating equation (3.7) with respect to y and multiplying both sides by $\frac{y}{\tilde{W}^*}$ we have:

$$\frac{\partial \tilde{W}^*}{\partial y} \frac{y}{\tilde{W}^*} = \frac{\partial A^*}{\partial y} \frac{y}{A^*} + \frac{y}{\sum_{j=1}^J S_j^*(y)W_j^*(y)} \left[\sum_{j=1}^J \frac{\partial S_j^*}{\partial y} W_j^*(y) + \sum_{j=1}^J S_j^*(y) \frac{\partial W_j^*}{\partial y} \right],$$

or

$$\eta_{\bar{W}} = \eta_A + \eta_{SW} + \eta_{WW} \quad (3.8)$$

where $\eta_{\bar{W}}$ is the percentage change in total water use at a given well with respect to a one percent change in well yield. η_A is the extensive margin effect that measures the percent change in water use through a change in irrigated acreage holding crop choices and water application depth per acre fixed. η_{SW} is the indirect intensive margin effect. It is the change in water application through changes in crop choice holding water application depth per acre and irrigated acres fixed. η_{WW} is the direct intensive margin effect. It is the change in water application depth per acre holding the crop choices and irrigated acres fixed.

3.3 Data

We model well-level decision making. Our unbalanced panel spans 1991-2014 and includes 6,261 unique wells overlaying the Kansas portion of High Plains Aquifer. Descriptive statistics are available in table 3.1.

Table 3.1. Descriptive statistics

Variable	Mean	Std. Dev.
Irrigated acres (acres)	132.50	89.80
Corn proportion	0.47	0.46
Soybeans proportion	0.10	0.28
Multiple crops proportion	0.17	0.37
Other crops proportion	0.26	0.40
Water application depth per acre (inches)	14.59	6.74
Well yield (gallons per minute)	579.70	342.14
Artificial well yield (gallons per minute)	2,218.75	1,895.08
Soil organic carbon in 0-150 cm depth (kg/m^2)	7,968.70	3,315.34
pH < 6	0.01	0.07
pH > 7.5	0.59	0.45
Root zone available water storage (mm)	239.77	58.53
Bulk density (g/cm^3)	1.41	0.13
Log of slope (%)	0.26	1.50
January to April Precipitation (mm)	115.11	57.49
May to August Precipitation (mm)	324.37	114.62
May to August Evapotranspiration (mm)	670.58	43.50

Historical water use data were obtained from Water Information Management and Analysis System (WIMAS) managed by Kansas Department of Agriculture's Division of Water Resources (KDA-DWR) and the Kansas Geological Survey (KGS). According to Kansas law, all water right holders are required to annually report their water use including irrigated acreage, crops grown, total water withdrawal and type of irrigation technology. We construct three dependent variables representing irrigation decisions: (i) total annual number of irrigated acres (extensive margin) (ii) probability of choosing each of the possible $j = 1, \dots, J$ crops (indirect intensive margin), and (iii) depth of water applied per acre conditional on crop choice (direct intensive margin).

Commonly grown crops in Kansas are corn, soybeans, sorghum, wheat and alfalfa. Other crops include oats, barley, rye, dry beans and sunflowers. Some farmers report "multiple crops" grown during a water use year. By "multiple" we understand more than one crop was grown, but which specific crops were chosen is not identified. Following Lee and Hendricks (2022), we reduce the crop choice to four field crops namely corn, soybeans, multiple crops and other crops. Alfalfa, wheat, and sorghum were combined into the other crops category.

A time series of well yields spanning 1991-2014⁵ was constructed using the method delineated in Chapter 2. Water well completion records (WWC5) in the state of Kansas are pivotal in calculation of well yields in this study. KGS maintains these records that contain crucial well and aquifer characteristics including well yields estimated at the time of construction, well depth and depth to static water level.

⁵ The temporal scope of this analysis was constrained by availability of water level data at the outset of the study. Future research could enhance the comprehensiveness of our findings by incorporating more recently available data.

Additionally, a time series of saturated thickness was obtained based on PLSS section-level water table elevation dataset obtained from KGS. This data set provides elevation of land surface, water table and bedrock. The vertical distance between the water table and bedrock was calculated to obtain section-level saturated thickness. PLSS section-level data on aquifer parameters namely hydraulic conductivity (K) and specific yield (S) were obtained from KGS. These data were then merged with relevant wells located within each section and subsequently used to construct the well yield variable as described in the previous chapter.

Time invariant soil characteristics including soil organic carbon, bulk density, proportion of cropland with pH less than 6 and pH greater than 7.5, root zone available water storage, and slope were obtained from the Soil Survey Geographic (SSURGO) Database. Time varying weather variables are from Parameter-elevation Regressions on Independent Slopes Model (PRISM) Database maintained by Oregon State University. Evapotranspiration (ET) constitutes the combined loss of water from soil surface through evaporation and from vegetation through transpiration. The irrigation requirement is defined as the difference between ET and available root zone soil moisture. Consequently, knowledge of ET is essential for optimizing irrigation scheduling. Reference evapotranspiration is generated using the Penman-Monteith method as outlined in Allen et al. (1998). We aggregate the precipitation and evapotranspiration data into pre growing season (January-April) and growing season (May-August) variables following Hendricks and Peterson (2012) and Lee and Hendricks (2022).

3.4 Econometric model

We use three econometric models to accommodate the effect of well yields on extensive irrigation margin, indirect intensive irrigation margin and direct intensive irrigation margin. Additionally, there is a reverse causality relationship between well yield and water use. Where

well yield affects farmers' decision about water use and the water use affects well yield by reducing saturated thickness of the aquifer. To resolve this endogeneity, we use aquifer characteristics that affect water use only through their effect on well yields as instruments. Specifically, we created predicted well yield variable that is only a function of exogenous variables. This predevelopment well yield variable depends only on hydrologic variables (i.e. hydraulic conductivity, specific yield and predevelopment saturated thickness) that are plausibly exogenous (see Perez-Quesada et al. (2024) for detailed rationale). We use this predevelopment well yield as an instrument for current well yield.

3.4.1 Extensive margin effect

Extensive margin effect of well yield is the change in total irrigated acres due to change in well yield holding crop choices and water application depth as fixed. Let A_{it} denote the irrigated acres for a given well i in year t we estimate the following two stage regression allowing the endogenous well yield variable to enter the regression non-linearly following Cameron and Trivedi (2005):

$$\left[\begin{array}{l} A_{it} = \alpha_1 + \beta_1 \widehat{y_{it}} + \beta_2 \widehat{y_{it}^2} + \boldsymbol{\gamma_1 X_{it}'} + \theta_t + \varepsilon_{it} \quad \dots 2nd \text{ stage} \\ \quad \quad \quad \uparrow \\ y_{it} = \alpha_2 + \lambda_1 z_i + \lambda_2 z_i^2 + \boldsymbol{\gamma_2 X_{it}'} + \theta_t + \epsilon_{it} \quad \dots 1st \text{ stage} \\ y_{it}^2 = \alpha_3 + \lambda_3 z_i + \lambda_4 z_i^2 + \boldsymbol{\gamma_3 X_{it}'} + \theta_t + \varepsilon_{it} \quad \dots 1st \text{ stage} \end{array} \right] \quad (3.9)$$

where, y_{it} is the yield for well i in year t . We include a quadratic function to account for the potential non-linear effect of well yield on irrigated acres. Instrumental variable z is the predevelopment well yield discussed above. It is only a function of hydrologic variables that are all exogenous. $\mathbf{X}_{it}$ is a vector of explanatory variables including time invariant soil characteristics and time varying weather characteristics. Soil characteristics include soil organic carbon, proportion of cropped area with pH less than six, proportion of cropped area with pH

greater than 7.5, root zone available water storage, bulk density, and log of slope. Weather variables include January to April precipitation, May to August precipitation, and May to August evapotranspiration. θ_t represents year fixed effects that account for macro shocks which affect all fields.

3.4.2 Indirect intensive margin effect

The indirect intensive margin effect pertains to choice between more water intensive and less water intensive crops holding irrigated acres and water application depth as fixed. We use control function approach (Train, 2009; Wooldridge, 2015) to account for endogeneity in discrete crop choice model⁶. Specifically, in the first stage we regress the endogenous well yield variable on instrument z and exogenous variables and predict residuals. In the second stage, we estimate the multinomial logit model by adding the predicted residuals from the first stage as explanatory variable:

$$\left[\begin{aligned} Prob(S_{it} = j) &= \frac{\exp(\alpha_4^j + \beta_4^j y_{it} + \delta_4^j \hat{u}_{it} + \gamma_4^j X_{it}' + \sum_m \mu_m^j S_{it-1,m})}{\sum_l \exp(\alpha_4^l + \beta_4^l y_{it} + \delta_4^l \hat{u}_{it} + \gamma_4^l X_{it}' + \sum_m \mu_m^l S_{it-1,m})} \quad \dots 2nd \text{ stage} \\ &\quad \uparrow \\ y_{it} &= \alpha_5 + \lambda_5 z_i + \gamma_5 X_{it}' + \theta_t + u_{it} \quad \dots 1st \text{ stage} \end{aligned} \right] \quad (3.10)$$

where, y_{it} is the yield for well i in year t , z_i is the predevelopment yield for well i , X_{it} and θ_t have the same explanation as that for (3.9). $\hat{u}_{it}$ is the residual, which captures variation in well

⁶ In an ideal scenario, the fractional crop choice model should be estimated using information on crop shares within each field. However, about one-third of the observations reported that the field was split among more than one crops without reporting specific acreage allocated to each crop. Therefore, following Hendricks and Peterson (2012), we adopted a simplifying assumption that if k crops were grown in a given field, the share of each crop would be $1/k$. This assumption, while practical, introduces measurement error in crop share estimates thus reducing reliability of fractional crop choice model.

yield that is not explained by exogenous instrument and the explanatory variables. $Prob(S_{it} = j)$ is the probability of selecting crop j at well i in year t with $j=1, 2, 3, 4$ for corn, soybeans, multiple crops and other crops respectively. $S_{it-1,m}$ is the lagged crop choice decision associated with well i .

3.4.3 Direct intensive margin effect

Direct intensive margin effect is the change in the water application depth holding irrigated acres and crop choice decisions as fixed. However, one potential econometric issue is endogeneity of crop choice i.e., fields with larger water use may be more likely to plant certain crops. Potential unobserved factors that affect crop choice may also affect water use. To address this endogeneity we use one year lagged crop choice of each crop as instrumental variable for current year crop choice following Lee and Hendricks (2022). Let W_{it} denote the water application depth for well i in year t , we estimate the following two stage regression model following Cameron and Trivedi (2005):

$$\left[\begin{array}{l} W_{it} = \alpha_6 + \beta_6 \widehat{y_{it}} + \beta_2 \widehat{y_{it}^2} + \gamma_6 \mathbf{X}_{it}' + \sum_j \phi_j \widehat{S_{itj}} + \theta_t + \mu_{it} \quad \dots 2nd \text{ stage} \\ y_{it} = \alpha_7 + \lambda_6 z_i + \lambda_7 z_i^2 + \gamma_7 \mathbf{X}_{it}' + \sum_m \phi_m S_{it-1,m} + \theta_t + u_{it} \quad \dots 1st \text{ stage} \\ y_{it}^2 = \alpha_8 + \lambda_8 z_i + \lambda_9 z_i^2 + \gamma_8 \mathbf{X}_{it}' + \sum_m \phi_m S_{it-1,m} + \theta_t + v_{it} \quad \dots 1st \text{ stage} \\ S_{itj} = \alpha_9 + \lambda_{10} z_i + \lambda_{11} z_i^2 + \gamma_9 \mathbf{X}_{it}' + \sum_m \phi_m S_{it-1,m} + \theta_t + \omega_{it} \quad \forall j \dots 1st \text{ stage} \end{array} \right] \quad (3.11)$$

where, S_{itj} is the crop choice for each well i in year t from among four choices (i.e. corn, soybeans, multiple crops and other crops). The term $\sum_m \phi_m S_{it-1,m}$ denotes one year lagged crop choices of each crop. The rest of the explanatory variables are the same as those used for estimating model (3.9). Since observations within the panel are likely to share similar

characteristics, we cluster standard errors by well to account for within cluster correlation of error terms in all models.

3.5 Results

3.5.1 Extensive margin effect

Table 3.2 illustrates results for the irrigated acres regression. The average marginal effect of well yield on irrigated acres is 0.135. This indicates that keeping all else equal, on average, a 100 GPM increase in well yield is associated with an increase of 13.5 irrigated acres. The negative coefficient on the squared well yield indicates that the effect of well yield on irrigated acres is diminishing (i.e., total irrigated acres increase at a decreasing rate with the increase in well yield).

Table 3.2. 2SLS regression results for irrigated acres model

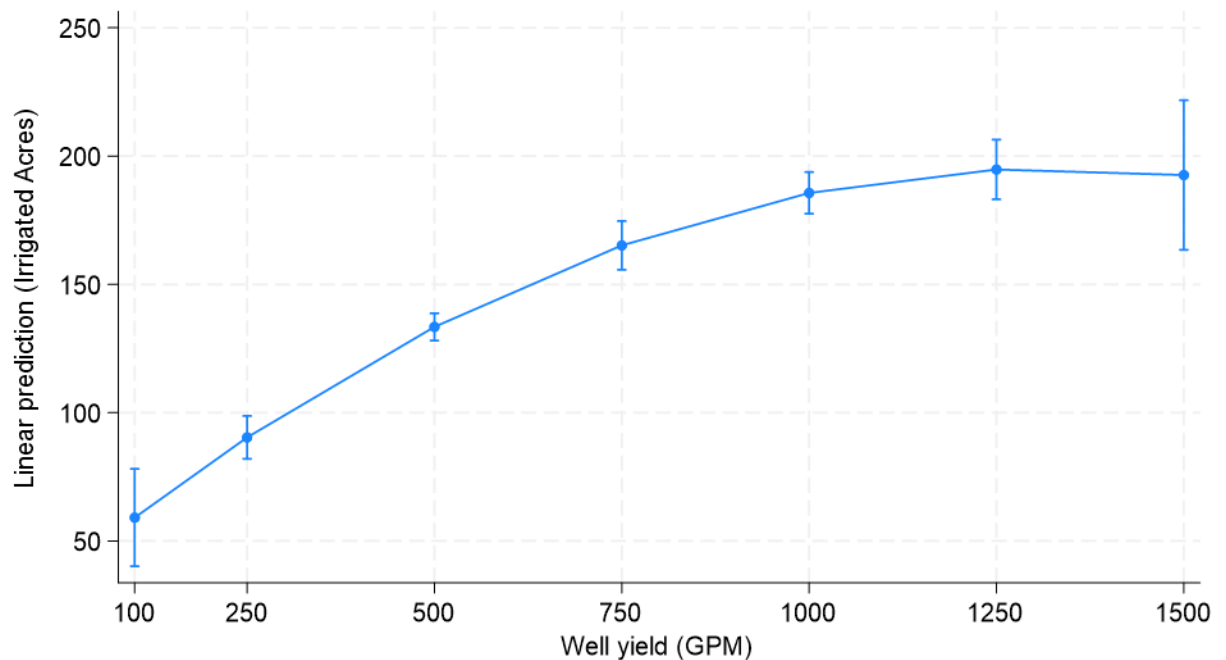
Variables	Coefficients
Well yield (GPM)	0.240*** (0.0487)
Squared well yield	-9.05e-05*** (3.20e-05)
Soil organic carbon in 0-150 cm depth (kg/m ²)	-0.00404*** (0.000388)
pH < 6	8.830 (14.33)
pH > 7.5	17.80*** (3.514)
Root zone available water storage (mm)	0.140*** (0.0360)
Bulk density (g/cm ³)	19.65 (19.85)
Log of slope (%)	-5.201*** (0.949)
January to April Precipitation (mm)	-0.126*** (0.0166)
May to August Precipitation (mm)	-0.0121* (0.00656)
May to August Evapotranspiration (mm)	0.496*** (0.0587)
Constant	-328.5*** (64.47)
Observations	106,357

R-squared	0.142
Year FE	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The nonlinear relationship is illustrated in Figure 3.1. This figure shows the averages of predictions of irrigated acres, holding well yield to each of its levels specified on the horizontal axis. At 250 GPM the value of predicted irrigated acres is 90.39. As the well yield increases to 750 GPM, we observe a significant jump in irrigated acres (from 90.39 to 165 acres). However, increasing well yield from 750 GPM to 1250 GPM only results in an additional 29 acres (from 165 to 194). Hence, each additional unit of well yield results in progressively smaller increase in irrigated acres. One possible explanation of this non-linear relationship is that at lower well yields, the risk of water stress at peak evapotranspiration stages is higher that significantly affects crop yields. Therefore, to avoid yield loss across larger acreage, farmers concentrate irrigation on fewer acres. Conversely, as the well yield becomes large the risk of water stress affecting crop yields significantly decreases and farmers expand irrigated acres to the point where either land or water availability constrains bind.

Figure 3.1. Linear prediction of irrigated acres against well yield



Weather variables all have the expected signs. An increase in precipitation results in a decrease in irrigated acres and an increase in evapotranspiration increases irrigated acres. The first stage regression results (Supplement to Chapter 3) indicate that the instrumental variables are strong and relevant with large F-statistics and statistically significant coefficients. The regression-based test of exogeneity of instruments yield a p-value of 0.00 indicating that OLS estimates are inconsistent due to endogeneity and the IV approach is preferred.

3.5.2 Indirect intensive margin effect

Table 3.3 presents the marginal effects on the probability of each crop choice from the multinomial logit model. The bootstrap standard errors are provided in parentheses. The marginal effects indicate how a unit change in the explanatory variables affect the probability of each crop choice. These marginal effects sum to 0 for each explanatory variable across crops. The “other crops” is used as the base category.

Table 3.3. Control function multinomial logit marginal effects for crop choice model

Variables	Corn	Soybeans	Multiple Crops	Other Crops
Well yield (GPM)	0.00031*** (0.00004)	-0.00003** (0.00001)	-0.00007*** (0.00003)	-0.00021*** (0.00003)
Control function	-0.00025*** (0.00004)	0.00002* (0.00001)	0.00008*** (0.00003)	0.00015*** (0.00004)
Soil organic carbon (kg/m2)	-0.00001*** (0.00000)	0.00001*** (0.00000)	0.00000 (0.00000)	0.00001*** (0.00000)
pH<6	0.07574 (0.05338)	0.02406 (0.01679)	-0.00485 (0.03042)	-0.09495** (0.03939)
pH>7.5	-0.03963*** (0.01287)	-0.04619*** (0.00502)	0.03542*** (0.00840)	0.05040*** (0.00992)
Root zone water storage	0.00145*** (0.00014)	-0.00003 (0.00006)	-0.00013 (0.00009)	-0.00129*** (0.00011)
Bulk density (g/cm3)	-0.14212** (0.07189)	0.21214*** (0.02771)	-0.07822* (0.04680)	0.00820 (0.05798)
Log of slope (%)	0.01781*** (0.00364)	-0.00852*** (0.00149)	-0.02305*** (0.00207)	0.01376*** (0.00300)
January to April precipitation	-0.00026** (0.00012)	0.00032*** (0.00004)	0.00016** (0.00008)	-0.00022** (0.00009)
May to August precipitation	-0.00010** (0.00004)	0.00002 (0.00002)	0.00008*** (0.00003)	0.00000 (0.00003)
May to August evapotranspiration	-0.00100*** (0.00024)	-0.00094*** (0.00009)	0.00111*** (0.00016)	0.00083*** (0.00019)
Lagged choice for corn	0.61508*** (0.01065)	0.05731*** (0.00409)	-0.13549*** (0.00621)	-0.53689*** (0.00900)
Lagged choice for soybeans	0.50170*** (0.01327)	-0.00000 (0.00602)	-0.08472*** (0.00881)	-0.41699*** (0.01148)
Lagged choice for multiple crops	0.01711 (0.01112)	-0.02235*** (0.00642)	0.33017*** (0.00708)	-0.32493*** (0.00853)
Year Fixed Effects	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Our results indicate that keeping all else equal, 100 GPM increase in well yield is associated with 3 percentage point increase in probability of planting corn, 0.3 percentage point decrease in probability of planting soybeans, 0.7 percentage point decrease in probability of planting multiple crops, and 2.1 percentage point decrease in probability of planting other crops. The observed positive relationship between well yield and the probability of planting corn (which is a water intensive crop) supports the hypothesis that higher well yield improves a

farmer's ability to ensure adequate soil moisture during critical growth stages, thereby increasing corn yields.

The marginal effects on lagged crop choice are also statistically significant. Planting corn in the previous year increases the probability of planting corn in the current year by 61.5 percentage points and soybeans by 5.7 percentage points compared to the choice of other crops in the previous year. The decision to plant corn in the previous year decreases the probability of planting multiple crops by 13.5 percentage points and other crops by 53.7 percentage points compared to the choice of planting other crops in the previous year. Similarly, the decision to plant soybeans in the previous year increases the probability of planting corn in the current year by 50.2 percentage points and decreases the probability multiple crops by 8.5 percentage points and other crops by 41.7 percentage points. The decision to plant soybeans in the previous year leads to minimal effect on the probability of planting soybeans in the current year. We used control function approach to correct for endogeneity in the multinomial crop choice model. The marginal effect of control function on crop choice is statistically significant, indicating the presence of endogeneity.

3.5.3 Direct intensive margin effect

Table 3.4 presents results for model (3.11) where the dependent variable is the water application depth. The average marginal effect of well yield on water application depth is 0.0047. This indicates that keeping all else equal, on average, a 100 GPM increase in well yield is associated with a 0.47 acre-inch increase in water application depth.

Table 3.4. 2SLS regression results for the depth applied model

Variables	Coefficients
Well yield (GPM)	0.00962*** (0.00344)
Squared well yield	-4.23e-06* (2.24e-06)

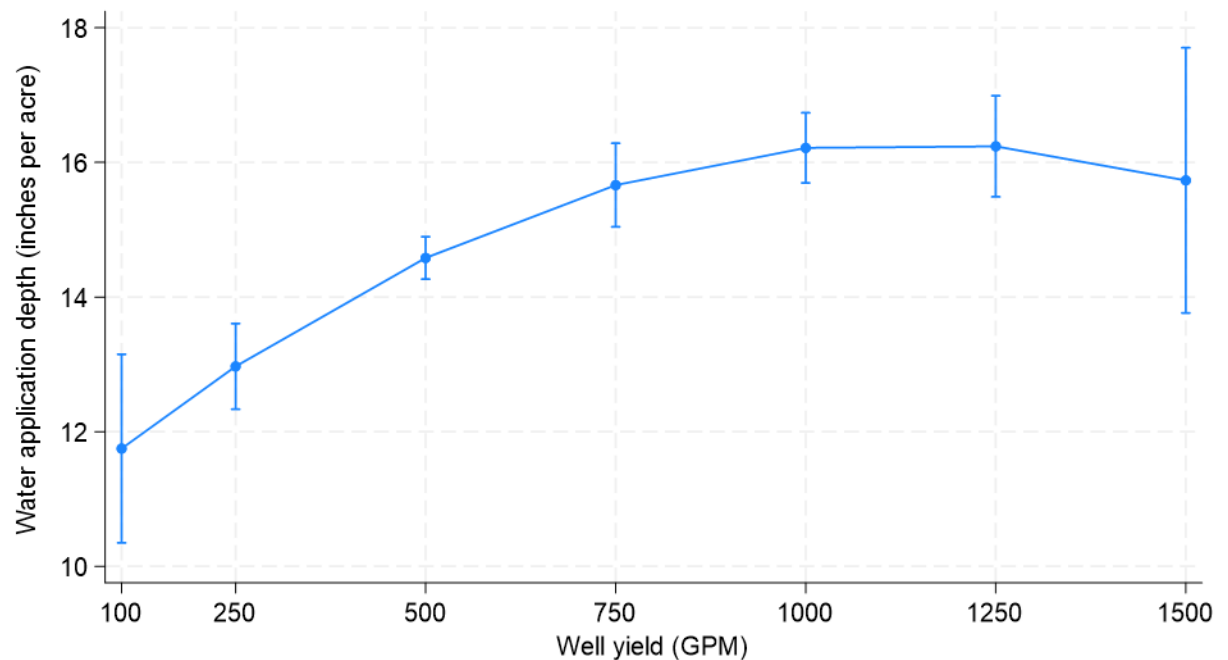
Corn	4.313*** (0.347)
Soybeans	-5.151*** (0.700)
Multiple crops	0.0385 (0.266)
Soil organic carbon in 0-150 cm depth (kg/m ²)	1.88e-05 (2.90e-05)
pH < 6	-4.542*** (0.721)
pH > 7.5	0.530** (0.228)
Root zone available water storage (mm)	-0.0329*** (0.00220)
Bulk density (g/cm ³)	1.497 (1.001)
Log of slope (%)	0.203*** (0.0599)
January to April precipitation (mm)	-0.0127*** (0.00122)
May to August precipitation (mm)	-0.0118*** (0.000478)
May to August evapotranspiration (mm)	0.0236*** (0.00398)
Constant	3.687 (3.910)
Observations	80,576
R-squared	0.130
Year FE	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 3.2 indicates that water application depth increases at a decreasing rate with the increase in well yield. At 250 GPM the predicted water application depth is 13 inches. As the well yield increases to 750 GPM, we observe a significant jump in depth applied (from 13 to 15.7 inches). However, increasing well yield from 750 GPM to 1250 GPM only results in an additional 0.57 inches (from 15.7 to 16.23 inches). Hence, each additional unit of well yield results in progressively smaller increase in water application depth.

Figure 3.2. Linear prediction of water application depth against well yield



A possible explanation of this non-linear relationship is that when well yield is low, increasing it has larger impact on farmers' ability to apply sufficient water during critical stages of crop growth leading to higher crop yield gains. Conversely, with higher well yields, the water stress at the peak evapotranspiration stages is minimal, so additional increments in water application do not translate into higher crop yield gains.

The coefficients on water application depth conditional on crop choice indicate that corn uses the most water. Also crop choice results in the previous section indicate that farmers tend to grow more corn with the increase in well yield. Considering these two results together implies that farmers tend to choose more water intensive crops with an increase in well yield.

Coefficients on weather variables exhibit expected signs. An increase in precipitation is associated with a decrease in water application depth keeping all else equal. Similarly, an

increase in evapotranspiration demand during the growing season is associated with an increase in water application depth.

3.5.4 Elasticity decomposition results

Table 3.5 reports the elasticity of water use with respect to well yield decomposed into extensive and intensive margins at three levels of well yield. Water use is most elastic at lower well yields and this elasticity decreases as well yields increase. Farmers facing well yield constraints primarily change their water use by adjusting irrigated acres and water application depth, whereas change in water use due to change in crop mix is relatively small.

Table 3.5. Decomposed elasticity of water use with respect to well yield

Well yield (GPM)	Extensive Margin Effect	Direct Intensive Margin Effect	Indirect Intensive Margin Effect	Total
250	0.54*** (0.09)	0.14*** (0.05)	0.01*** (0.00)	0.70*** (0.10)
750	0.47*** (0.03)	0.16*** (0.02)	0.03*** (0.00)	0.66*** (0.04)
1250	0.09 (0.21)	-0.07 (0.17)	0.05*** (0.00)	0.06 (0.27)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

At 250 GPM, a 10% increase in well yield leads to a 5.4% increase in water use through changes in irrigated acres, 1.4% increase in water application depth, and 0.1% increase in water use due to a change in crop mix. Combined these three factors lead to a 7% increase in total water use. At 750 GPM, a 10% increase in well yield leads to a 4.7% increase in water use through changes in irrigated acres, 1.6% increase in water application depth, and 0.3% increase in water use due to a change in crop mix. Overall, these three adjustments lead to a 6.6% increase in total water use. At 1250 GPM, the effect of change in well yield on irrigated acreage and water application depth becomes statistically insignificant, whereas we observe a small increase in water use due to a shift towards more water intensive crops. Overall, the effect of a change in well yield on total water use is insignificant at 1250 GPM. These results indicate that

at low and moderate well yields the dominant response is irrigated acreage expansion followed by increased water application depth. An increase in well yield improves farmers' ability to meet intra-season crop water demand more effectively through optimal irrigation scheduling. At 1250 GPM, well yield is not a binding constraint, and the water use may be dictated by the land or water availability constraints rather than the well yield.

3.5.5 The Effect of ignoring endogeneity of well yields

In section 3.4 we discussed the reverse causality relationship between well yield and water use where well yield affects farmers' decision about water use and the water use affects well yield by reducing saturated thickness of the aquifer. Because of the negative feedback effect of water use on well yields we expect coefficients on well yield to be biased downwards in specifications ignoring endogeneity of well yields. In this section we discuss how our results change if we do not account for endogeneity of well yields.

3.5.5.1 Extensive margin effect

Table 3.6 illustrates coefficients for OLS (ignoring endogeneity) and 2SLS instrumental variable regressions with irrigated acreage as the dependent variable. The 2SLS coefficients on the well yield and squared well yield variables are larger than the OLS estimates (71% for well yield and 125% for squared well yield). We also report test statistics for the test of endogeneity which examines the null hypothesis that well yield and squared well yield are exogenous. The test statistic (11.18) is significant at the 1% level, indicating the downward bias of OLS from feedback effect is statistically significant. Furthermore, the value of F-statistics testing the null hypothesis that the instrumental variables are equal to zero in the first stage regression are significantly large (366.08 and 130.20) indicating the instrumental variables are not weak.

Table 3.6. OLS and 2SLS regression results for irrigated acres model

Variables	OLS	2SLS
-----------	-----	------

Well yield (GPM)	0.14032*** (0.00755)	0.24007*** (0.04870)
Squared well yield	-0.00004*** (0.00000)	-0.00009*** (0.00003)
Soil organic carbon in 0-150 cm depth (kg/m2)	-0.00390*** (0.00037)	-0.00404*** (0.00039)
pH < 6	13.08788 (13.86547)	8.82969 (14.32807)
pH > 7.5	14.20366*** (3.02532)	17.79835*** (3.51359)
Root zone available water storage (mm)	0.15226*** (0.03243)	0.14041*** (0.03599)
Bulk density (g/cm3)	23.81377 (18.81317)	19.65224 (19.84568)
Log of slope (%)	-5.69828*** (0.83909)	-5.20148*** (0.94901)
January to April precipitation (mm)	-0.12009*** (0.01531)	-0.12594*** (0.01657)
May to August precipitation (mm)	-0.01166** (0.00573)	-0.01212* (0.00656)
May to August evapotranspiration (mm)	0.48854*** (0.04891)	0.49624*** (0.05872)
Constant	-296.67079*** (50.78232)	-328.49067*** (64.46933)
F-statistic for IVs in first stage		366.08
Test for endogeneity		130.20
Observations	107,349	106,357
R-squared	0.19165	0.14234
Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.5.5.2 Indirect intensive margin effect

Table 3.7 illustrates the marginal effects on the probability of each crop choice from the multinomial logit model when ignoring endogeneity of well yields. The marginal effects on the probability of crop choices with respect to a unit change in well yields when ignoring endogeneity are smaller compared to those estimated by correcting for endogeneity.

Table 3.7. Multinomial logit marginal effects for crop choice model-ignoring endogeneity

Variables	Corn	Soybeans	Multiple Crops	Other Crops
Well yield (GPM)	0.00009*** (0.00001)	-0.00001** (0.00001)	-0.00000 (0.00001)	-0.00007*** (0.00001)

Soil organic carbon (kg/m2)	-0.00001*** (0.00000)	0.00001*** (0.00000)	-0.00000 (0.00000)	0.00001*** (0.00000)
pH<6	0.08768* (0.04904)	0.02204 (0.01608)	-0.00681 (0.02889)	-0.10291*** (0.03443)
pH>7.5	-0.02627** (0.01197)	-0.04671*** (0.00498)	0.02962*** (0.00836)	0.04335*** (0.00922)
Root zone water storage	0.00152*** (0.00013)	-0.00005 (0.00006)	-0.00016* (0.00009)	-0.00132*** (0.00011)
Bulk density (g/cm3)	-0.03187 (0.06626)	0.20448*** (0.02761)	-0.12119*** (0.04436)	-0.05142 (0.05456)
Log of slope (%)	0.01405*** (0.00342)	-0.00873*** (0.00135)	-0.02128*** (0.00206)	0.01597*** (0.00287)
January to April precipitation	-0.00012 (0.00011)	0.00031*** (0.00004)	0.00010 (0.00007)	-0.00030*** (0.00009)
May to August precipitation	-0.00007* (0.00004)	0.00001 (0.00002)	0.00008*** (0.00003)	-0.00002 (0.00003)
May to August evapotranspiration	-0.00072*** (0.00022)	-0.00103*** (0.00009)	0.00107*** (0.00016)	0.00068*** (0.00017)
Lagged choice for corn	0.62621*** (0.01033)	0.05735*** (0.00404)	-0.13942*** (0.00620)	-0.54415*** (0.00822)
Lagged choice for soybeans	0.51503*** (0.01267)	-0.00360 (0.00610)	-0.08932*** (0.00893)	-0.42211*** (0.01081)
Lagged choice for multiple crops	0.02865*** (0.01049)	-0.02339*** (0.00630)	0.32497*** (0.00671)	-0.33022*** (0.00801)
Observations	67,173	67,173	67,173	67,173
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.5.5.3 Direct Intensive margin effect

Tables 3.8 illustrates estimates for OLS and 2SLS regressions with water application depth as the dependent variable. The coefficient on the linear well yield variable in the 2SLS model is 117% larger than that in the OLS model. The test statistic for endogeneity is 56.61, which is significant at the 1% level indicating that downward bias from feedback effect is statistically significant.

Table 3.8. OLS and 2SLS regression results for the depth applied model

Variables	OLS	2SLS
Well yield (GPM)	0.00443*** (0.00050)	0.00962*** (0.00344)
Squared well yield	-0.00000*** (0.00000)	-0.00000* (0.00000)
Corn	2.47673*** (0.10179)	4.31339*** (0.34654)

Soybeans	0.73884*** (0.10269)	-5.15139*** (0.70048)
Multiple crops	0.37603*** (0.13607)	0.03850 (0.26590)
Soil organic carbon in 0-150 cm depth (kg/m2)	-0.00010*** (0.00002)	0.00002 (0.00003)
pH < 6	-4.42852*** (0.61055)	-4.54242*** (0.72083)
pH > 7.5	0.93826*** (0.17960)	0.52996** (0.22846)
Root zone available water storage (mm)	-0.02722*** (0.00191)	-0.03294*** (0.00220)
Bulk density (g/cm3)	1.69207* (0.95069)	1.49678 (1.00089)
Log of slope (%)	0.23930*** (0.04842)	0.20273*** (0.05992)
January to April precipitation (mm)	-0.01804*** (0.00103)	-0.01268*** (0.00122)
May to August precipitation (mm)	-0.01112*** (0.00041)	-0.01183*** (0.00048)
May to August evapotranspiration (mm)	0.02925*** (0.00292)	0.02362*** (0.00398)
Constant	5.04118* (2.69335)	3.68749 (3.90961)
F-statistic for IVs in first stage		132.75 52.43 3032.98 382.44 1794.31 56.61***
Test for endogeneity		
Observations	87,166	80,576
R-squared	0.25975	0.12975
Year FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.5.5.4 Elasticity estimates

Table 3.9 illustrates the elasticity estimates when ignoring endogeneity of well yields. At 250 GPM the extensive margin elasticity is 0.30, which is 44% less than the 0.54 estimated when correcting for endogeneity of well yields. Similarly, the overall elasticity is 47% less (0.37 vs. 0.70) when ignoring endogeneity. Similarly, at 750 GPM extensive margin elasticity is 12% less (0.42 vs. 0.47) and overall elasticity is 22% less (0.52 vs. 0.66).

Table 3.9. Elasticity of water use with respect to well yield – ignoring endogeneity

Well yield (GPM)	Extensive Margin Effect	Direct Intensive Margin Effect	Indirect Intensive Margin Effect	Total
250	0.30*** (0.01)	0.07*** (0.01)	0.00*** (0.00)	0.37*** (0.02)
750	0.42*** (0.02)	0.10*** (0.01)	0.00*** (0.00)	0.52*** (0.02)
1250	0.32*** (0.04)	0.03 (0.02)	0.00*** (0.00)	0.36*** (0.04)

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

3.5.6 Robustness to ignoring crop choice

In our water application depth regression (3.11), we used lagged crop choices as instrumental variables for current crop choices. The exclusion restriction requires that lagged crop choices affect water application depth only through their impact on current crop choices. The exclusion restriction may be violated in two ways: (1) if past crop choices influence current water use independently of current crop choice (e.g., due to soil moisture retention), then lagged crop choices affect water use directly, not just through current crop choice; (2) if there are unobserved time varying factors (e.g. irrigation system upgrades) that affect both past crop choice and current water use, then lagged crop choices could be correlated with the error term. As a robustness check we adopt an alternative specification where we do not control for crop choice in the depth applied regression. The total optimal water use $\widetilde{W}^*(y)$ as presented in equation (3.7) is modified as:

$$\widetilde{W}^*(y) = A^*(y)W^*(y), \quad (3.12)$$

where $A^*(y)$ denotes optimal irrigated acres and $W^*(y)$ denotes optimal water application depth.

Differentiating both sides with respect to y and multiplying with $\frac{y}{\widetilde{W}^*}$ we have:

$$\frac{\partial \widetilde{W}^*}{\partial y} \frac{y}{\widetilde{W}^*} = \frac{\partial A^*}{\partial y} \frac{y}{A^*} + \frac{\partial W^*}{\partial y} \frac{y}{W^*},$$

or

$$\eta_{\bar{W}} = \eta_A + \eta_W, \quad (3.13)$$

where η_A is the extensive margin elasticity and η_W is the total intensive margin elasticity. Table 3.13 (supplement to chapter 3) shows coefficients for the water application depth regression without crop choice controls. Table 3.10 illustrates decomposed elasticity of water use with respect to well yield. The elasticities are similar to those presented in table 3.5. Therefore, concerns about lagged crop choices violating the exclusion restriction do not have a significant impact on our findings.

Table 3.10. Decomposed elasticity of water use with respect to well yield – excluding crop choice

Well yield (GPM)	Extensive Margin Effect	Intensive Margin Effect	Total
250	0.54*** (0.09)	0.16*** (0.03)	0.70*** (0.10)
750	0.47*** (0.03)	0.23*** (0.02)	0.71*** (0.04)
1250	0.09 (0.21)	0.14 (0.11)	0.23 (0.24)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6 Effect of well yield on irrigation technology adoption

In the previous sections, we established empirical evidence on how limited well yields affect optimal water use. However, it remains unclear whether the impact of well yields extends beyond decisions about water use to also influence decisions about water use efficiency, specifically the adoption of efficient irrigation technology. In this section, we test the hypothesis that in regions with low to moderate well yields, the adoption of efficient irrigation technology is higher compared to regions with higher well yields.

We model farmers' irrigation technology adoption decision using duration analysis (Cox, 1972; Cleves, 2008) which focuses on timing of events rather than just whether they occur. Duration models have been widely applied in agricultural economics to study adoption of innovations (Griliches, 1957; Burton et al., 2003; Dadi et al., 2004; Abdulai & Huffman, 2005; D'Emden et al., 2006; Prokopy et al., 2019). We examine the length of time a farmer uses current irrigation technology before switching to a new one. Specifically we evaluate two sequential adoption events: (1) transition from flood to center pivot irrigation system, and (2) transition from standard center pivot to center pivot with low drop nozzles. For each transition we define a hazard function $h_i(t)$ for farm i at time t , which is the instantaneous probability of adoption (the event) at time t given that the farm has not yet adopted the new technology prior to t . The cox proportional hazard model (Cox, 1972) can be written as:

$$h_i(t) = h_0(t) \exp\{\beta_1 y_{it} + \beta_2 y_{it}^2 + \gamma_1 \mathbf{X}_{it}' + \theta_t\} \quad (3.14)$$

where $h_0(t)$ is the baseline hazard function (the hazard rate when all covariates are zero), y denotes the well yield, $\mathbf{X}_{it}$ is a vector of explanatory variables including time invariant soil characteristics and time varying weather characteristics, and θ_t represents year fixed effects that

account for macro shocks which affect all fields. Time is measured in years and we know the exact year each farmer adopted a new technology.

3.6.1 Transition from flood to center pivot

Table 3.11 illustrates the cox proportional hazard model estimates for the timing of adoption for transition from flood irrigation system to center pivot irrigation system. The coefficient on well yield is significantly positive and that on squared well yield is significantly negative indicating that relative hazard of adopting center pivot increases at a decreasing rate. The average value of well yield is 620 GPM. At this mean well yield, the hazard ratio (HR) is 1.901 calculated as $HR_{\bar{y}} = \exp(\beta_1\bar{y} + \beta_2\bar{y}^2)$, where $\bar{y}$ represents mean well yield. This indicates that the hazard of adoption at 620 GPM is 90% higher than the baseline scenario of 0 GPM. Based on (Cleves, 2008) the marginal effect of well yield on log hazard is $\frac{\partial \log h(t)}{\partial y} = \beta_1 + \beta_2 y$ meaning the marginal hazard ratio (MHR) at mean would be $\exp(\beta_1 + \beta_2\bar{y})$. The MHR at mean is 1.030 meaning on average, holding other variables constant, 100 GPM increase in well yield from 620 GPM is associated with a 3% increase in hazard of adopting center pivot irrigation system. Figure 3.3 illustrates that the relative hazard of adopting center pivot increases up to 750 GPM and then starts to decrease. The underlying mechanism behind the nonlinear relationship between well yield and the relative hazard of adopting center pivot irrigation system is the change in elasticity of water use with respect to well yield. At low to moderate well yields, water use is highly elastic – well yield is the binding constraint and farmers can benefit significantly from adopting center pivot system, which allows them to reduce water application depth per acre while maintaining crop yields and irrigated acres. However, at higher well yields, water availability is no longer a limiting factor, and farmers can continue using flood irrigation

system without compromising irrigated acreage or crop yields. As a result, the economic incentive to adopt center pivot system diminishes when yield is sufficiently large.

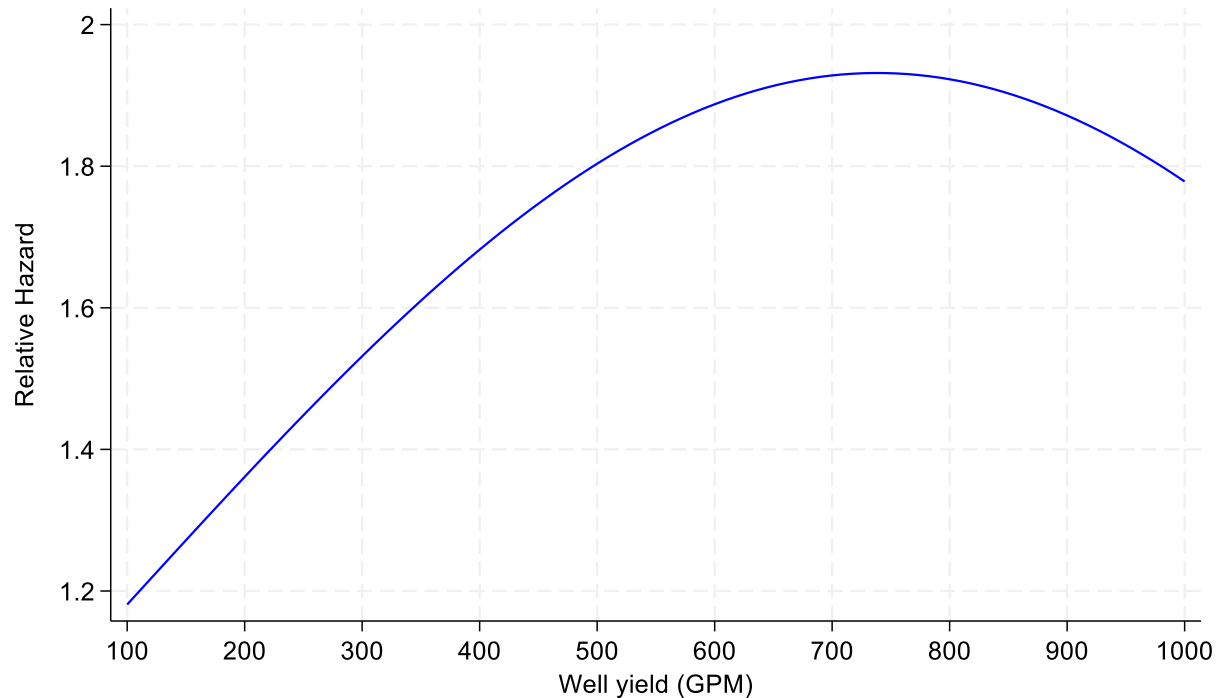
Table 3.11. Cox model estimates for timing of adoption of center pivot irrigation system

Variables	Coefficients	Hazard ratios
Well yield (100 GPM)	0.178*** (0.0489)	1.030***
Squared well yield	-0.0121*** (0.00346)	
Authorized irrigated acres	0.000179** (7.12e-05)	1.000179**
Deviation in precipitation from county average	0.00464 (0.00316)	1.004652
Deviation in evapotranspiration from county average	0.0528 (0.0328)	1.054235
Sandy soil	4.165*** (0.759)	64.36068***
Soil organic carbon	-7.33e-05*** (1.70e-05)	.9999267***
pH>7.5	0.378** (0.172)	1.460081**
Root zone available water storage	0.00709*** (0.00170)	1.00711***
Bulk density	0.314 (0.636)	1.369279
Log of slope (%)	0.0340 (0.0258)	1.034549
Observations	10,013	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 3.3. Predicted hazard ratio vs well yield



3.6.2 Transition from standard center pivot to center pivot with low drop nozzles

Table 3.12 illustrates the cox proportional hazard model estimates for the timing of adoption for transition from standard center pivot irrigation system to center pivot irrigation system with low drop nozzles. The coefficients on both well yield and squared well yield are insignificant indicating that well yield does not have a significant impact on timing of adoption of center pivot with low drop nozzles. In other words, once a farmer has already committed to a center pivot system, well yield stops being a binding constraint, and the decision to upgrade to low drop nozzles is driven by a different set of factors. The decision to adopt low drop nozzles is primarily related to improved water application and energy efficiency (Rogers et al., 2008) and is not constrained by well yields.

Table 3.12. Cox model estimates for timing of adoption of center pivot with low drop nozzles

Variables	Coefficients	Hazard ratios
Well yield (100 GPM)	0.0301 (0.0292)	1.025
Squared well yield	-0.00267 (0.00202)	
Authorized irrigated acres	3.28e-06 (5.21e-05)	1.00
Deviation in precipitation from log time county average	-0.00575*** (0.00179)	0.994***
Deviation in evapotranspiration from log time county average	-0.0304* (0.0169)	0.970*
Sandy soil	0.125 (0.106)	1.133
Soil organic carbon	-1.41e-05 (9.57e-06)	0.999
pH<6	-0.180 (0.265)	0.835
pH>7.5	-0.0940 (0.0643)	0.910
Root zone available water storage	0.00115 (0.000772)	1.00
Bulk density	-1.053*** (0.367)	0.349***
Log of slope (%)	0.0822*** (0.0190)	1.086***
Observations	25,775	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.6.3 Limitations of technology transition model

Our technology adoption model has certain limitations. While we control for authorized irrigated acres at well level and soil characteristics, we are unable to fully account for farm-level heterogeneity. Specifically, variables such as farmer age, education, farm income, and risk preferences are not included in the model due to data availability constraints. These omitted variables are known to influence both the decision to adopt new technologies and the timing of

adoption (Prokopy et al., 2019). If this unobserved heterogeneity is correlated with well yield (for example, if wealthier farmers are located in areas with lower well yields and are more likely to adopt center pivot irrigation system), our estimates will be biased.

Another potential critique of our model is the possibility of reverse causality between irrigation technology adoption and well yield – specifically, that improved efficiency may lead to increased water use through rebound effect (Pfeiffer & Lin, 2014). This would raise concern about the endogeneity of well yield. However, a recent empirical study by Cameron-Harp and Hendricks (2025) found that adoption of improved irrigation technology led to a small and statistically insignificant decrease in water use in the HPA region of Kansas. While this provides some reassurance, we acknowledge that the strength of this relationship may vary across regions and institutional settings.

A further limitation of our technology adoption model is the omission of peer effects. Spatially mediated peer effects are widely acknowledged as a significant factor in technology adoption decisions. For instance, Sampson and Perry (2019b) provide empirical evidence on how peer influence substantially affects farmers’ adoption of groundwater for irrigation. Their findings indicate that one additional neighbor adopting groundwater for irrigation raises the likelihood of adoption by an average of 0.25 percentage points. Similarly, Sampson and Perry (2019a) show how peer effects influence diffusion of low energy precise application (LEPA) technology. Their findings indicate that an additional LEPA installation within 1km radius increases the probability of adoption by 0.3 percentage points, with this influence decreasing with the distance between neighboring farmers.

3.7 Supplement to Chapter 3

Table 3.13. 2SLS regression results for the depth applied model – excluding crop choice

Variables	Coefficients
Well yield (GPM)	0.00942*** (0.00242)
Squared well yield	-0.00000* (0.00000)
Soil organic carbon (kg/m2)	-0.00012*** (0.00002)
pH<6	-4.29513*** (0.74624)
pH>7.5	0.53464*** (0.19961)
Root zone water storage	-0.02313*** (0.00203)
Bulk density (g/cm3)	-0.81599 (1.00489)
Log of slope (%)	0.32836*** (0.05221)
January to April precipitation	-0.01852*** (0.00107)
May to August precipitation	-0.01228*** (0.00043)
May to August evapotranspiration	0.02101*** (0.00335)

Constant	12.36577*** (3.38524)
Observations	95,925
R-squared	0.21221
Year FE	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.14. First stage regressions for 2SLS irrigated acres model

Variables	Well Yield	Well Yield Squared
Predevelopment well yield (GPM)	0.157*** (0.00958)	186.8*** (39.02)
Predevelopment well yield Squared	-9.69e-06*** (1.30e-06)	-0.00673 (0.00596)
Soil organic carbon (kg/m2)	0.0134*** (0.00193)	19.12*** (4.026)
pH < 6	62.42 (48.40)	63,308 (70,968)
pH > 7.5	85.76*** (15.87)	201,059*** (40,672)
Root zone water storage (mm)	0.395** (0.175)	569.1 (467.5)
Bulk density (g/cm3)	192.4** (77.93)	317,730** (160,847)
Log of slope (%)	10.60*** (3.483)	27,769*** (6,309)
January to April precipitation	0.433*** (0.0738)	718.7*** (154.5)
May to August precipitation	0.237*** (0.0257)	462.8*** (62.10)
May to August evapotranspiration	1.606*** (0.237)	3,598*** (605.4)
Constant	-1,334*** (216.8)	-3.290e+06*** (465,632)

F-statistic for IVs	366.08	130.20
Observations	106,357	106,357
R-squared	0.206	0.123
Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.15. First stage regression for multinomial logit crop choice model

Variables	Well Yield
Predevelopment well yield (GPM)	0.0629*** (0.00410)
Soil organic carbon (kg/m2)	0.0119*** (0.00222)
pH < 6	79.87 (53.13)
pH > 7.5	54.68*** (16.22)
Root zone water storage (mm)	0.286 (0.181)
Bulk density (g/cm3)	196.6** (85.05)
Log of slope (%)	5.788 (3.965)
January to April precipitation	0.478*** (0.0786)
May to August precipitation	0.180*** (0.0277)
May to August evapotranspiration	1.321*** (0.250)
Lagged crop choice for corn	45.14*** (7.736)
Lagged crop choice for soybeans	40.14*** (8.408)
Lagged crop choice for multiple crops	43.37***

Constant	(9.941) -909.7***
F-statistic for IVs	(224.1) 235.94
Observations	83,034
R-squared	0.154
Year FE	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.16. First stage regressions for 2SLS depth applied model

Variables	Well Yield	Well Yield Squared	Corn	Soybeans	Multiple Crops
Predevelopment well yield (GPM)	0.154*** (0.00703)	215.2*** (15.35)	3.28e-05*** (2.98e-06)	-6.85e-06** (2.69e-06)	-7.24e-06*** (2.07e-06)
Predevelopment well yield squared	-1.02e-05*** (7.68e-07)	-0.0121*** (0.00189)	-2.13e-09*** (2.88e-10)	4.58e-10 (2.99e-10)	4.70e-10** (1.92e-10)
Lagged choice for corn	31.93*** (6.439)	22,419* (11,649)	0.482*** (0.00586)	0.140*** (0.00470)	-0.0272*** (0.00258)
Lagged choice for soybeans	22.60*** (7.425)	22,104 (16,504)	0.306*** (0.00770)	0.237*** (0.00925)	-0.00355 (0.00323)
Lagged choice for multiple crop	43.70*** (9.735)	64,741*** (19,520)	-0.0645*** (0.00710)	0.0466*** (0.00440)	0.582*** (0.00721)
Soil organic carbon	0.0149*** (0.00214)	21.58*** (4.600)	-8.34e-06*** (1.06e-06)	1.34e-05*** (1.02e-06)	-2.29e-06*** (7.05e-07)
pH < 6	62.45 (51.12)	71,101 (74,194)	0.0870*** (0.0314)	0.0111 (0.0242)	0.0146 (0.0130)
pH > 7.5	60.92*** (15.92)	147,295*** (31,404)	0.0223*** (0.00772)	-0.0684*** (0.00693)	0.0138*** (0.00484)
Root zone water storage (mm)	0.270 (0.175)	582.6* (347.3)	0.00129*** (8.02e-05)	-0.000340*** (7.28e-05)	7.93e-06 (5.58e-05)
Bulk density (g/cm3)	105.2 (81.66)	140,135 (155,248)	-0.0733* (0.0409)	0.0970*** (0.0334)	-0.0346 (0.0299)
Log of slope (%)	11.37*** (3.805)	32,844*** (6,954)	0.0110*** (0.00201)	-0.0140*** (0.00155)	-0.0141*** (0.00153)

January to April precipitation	0.461*** (0.0753)	797.3*** (154.5)	-0.000265*** (6.25e-05)	0.000511*** (5.08e-05)	0.000103*** (3.96e-05)
May to August precipitation	0.170*** (0.0268)	339.2*** (56.18)	-6.79e-05*** (2.50e-05)	-2.89e-05 (2.07e-05)	8.78e-05*** (1.62e-05)
May to August evapotranspiration	1.052*** (0.236)	2,577*** (516.3)	-0.000174 (0.000133)	-0.00141*** (0.000113)	0.000827*** (8.97e-05)
Constant	-758.1*** (214.9)	-2.235e+06*** (423,924)	0.284** (0.115)	0.735*** (0.0968)	-0.557*** (0.0781)
F-statistic for IVs	132.75	52.43	3032.98	382.44	1794.31
Observations	84,898	84,898	84,795	84,795	84,795
R-squared	0.200	0.128	0.315	0.175	0.407
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 4 – Well interference and its farm level consequences

4.1 Introduction

Groundwater pumping externalities have been extensively discussed in the literature. Most studies represent pumping externalities either as an increase in pumping cost through lower aquifer levels (Gisser & Sanchez, 1980; Feinerman & Knapp, 1983; Rubio & Casino, 2001; Guilfoos et al., 2013; Guilfoos et al., 2016) or stock externalities (Provencher & Burt, 1993; Merrill & Guilfoos, 2018). The externality arising from reduced well yield due to pumping at neighboring wells has largely been ignored. Manning and Suter (2019) provide an exception, who numerically simulate a three-well hydro-economic model that allows for changes in saturated thickness due to pumping at neighboring wells to affect productivity of groundwater. Although Manning and Suter (2019) acknowledge that well yield is the driving force behind changing productivity of water, they do not explicitly model the hydrology that determines well yield or the change in well yield due to pumping at neighboring wells.

Earlier economic studies relied on “single-cell” or “bathtub” aquifer models that assume pumping by one user instantly and uniformly reduces the available water for all users, thus increasing their pumping cost (Gisser & Sanchez, 1980; Feinerman & Knapp, 1983; Negri, 1989; Provencher & Burt, 1993; Burness & Brill, 2001; Rubio & Casino, 2001; Koundouri, 2004). Recent studies recognize the spatially explicit nature of the groundwater resource and acknowledge that hydrological rules govern the movement of groundwater across space (Saak & Peterson, 2007; Brozović et al., 2010; Pfeiffer & Lin, 2012; Guilfoos et al., 2013; Peterson & Saak, 2018; Manning & Suter, 2019). These studies recognize that pumping externalities dissipate with the distance between the neighboring wells.

When a groundwater well operates within the radius of influence of another well, the overlapping cones of depression create additional drawdown, referred to as well interference drawdown (Kasenow, 2001). In the area where these cones intersect, the total drawdown is the combined effect of the drawdowns from both wells. As a result, the closer the wells are located to each other, the greater the interference and the lower the well yield of each well (Kasenow, 2001). Supporting this premise is a court case in Haskell County, Kansas, where the district court found that interference from neighboring junior water rights caused significant drawdown in a senior well – impairing its ability to pump authorized amount of water – and therefore, issued a permanent injunction on pumping from junior water rights (Garetson Brothers v. American Warrior, Inc. 2019).

Overlapping cones of depression cause wells to compete for the same water. Therefore, in order to accurately account for the impact of pumping on neighboring wells, explicitly modelling the cones of depression is the most reliable way to quantify well interference (Kasenow, 2001). Despite recognizing the spatially explicit nature of groundwater, recent studies ignore the extent of the overlap between cones of depression of neighboring wells.

This paper is the first to estimate the change in well yield due to pumping at neighboring wells across an entire region using well level hydrological data and the first to estimate how pumping at neighboring wells translate into changes in water use at the farm level.

4.2 Data and methods

4.2.1 Estimation of well yields and spillover effects

A time series of well yields from 1991 to 2014 was calculated using the methodology outlined in Chapter 2. The calculation of well yields in this study relies on water well completion records (WWC5) from Kansas. These records, maintained by Kansas Geological Survey (KGS)

include essential well and aquifer characteristics such as estimated well yields at the time of drilling, well depth and the static water level.

A time series of saturated thickness for the well yield calculation was obtained from the Public Land Survey System (PLSS) section-level water table elevation data set from KGS. The saturated thickness at section-level was calculated as the vertical distance between the water table and bedrock. Similarly, PLSS section-level data on aquifer parameters, hydraulic conductivity (K) and specific yield (S) were also obtained from KGS. These data were merged with relevant wells located within each section and used to calculate well yield.

For the calculation of well yield spillover effect, we calculated well yields with actual neighbors and those under a counterfactual scenario assuming all wells having no neighbors separately. For the calculation of well yield with neighbors, we calculated the number of neighboring wells within a 0.75 mile radius and assumed that these wells are all located at 0.5 mile distance from the target well. The well yield spillover effect was calculated as the percentage difference between well yield without neighbors and well yield with neighbors, thus for a given well i in year t :

$$Spillover_{it} = 100 \times \frac{Well\ yield\ without\ neighbors_{it} - Well\ yield\ with\ neighbors_{it}}{Well\ yield\ without\ neighbors_{it}} \quad (4.1)$$

Further, to simulate the effect of neighboring wells on water use we calculated well yields under multiple counterfactual scenarios by assuming 0, 2, 4, 6, 8, and 10 neighbors, each located at 0.5 mile distance from each well. These calculations are in addition to well yields calculated with actual neighbors.

4.2.2 Extensive and intensive irrigation margin effect of neighbors

We assume that pumping at neighboring wells causes additional drawdown at each target well thereby reducing transmissivity and hence well yield of the own well (Kasenow, 2001). This

reduction in well yield affects water use decisions based on the economic mechanisms outlined in Chapter 3. To estimate the effect of neighbors on extensive and intensive irrigation margin decisions, we used the econometric models (3.9-3.11) to predict the irrigated acres, probability of crop choice and water application depth for each crop using well yields described in the previous section.

4.3 Impact of neighbors on well yield

Table 4.1 provides a comparison of well yields with and without neighbors. The average well yield without neighbors (counterfactual scenario where all wells have no neighbors) in 1991 was 782 GPM and that with neighbors in 1991 was 638 GPM. Similarly, average well yield without neighbors in 2014 was 605 GPM and that with neighbors was 506 GPM. These results indicate that well yields have declined over time and the well yields with neighbors are significantly less than those without neighbors. This is consistent with the theory; intersecting cones of depression cause additional drawdown in the aquifer thereby reducing transmissivity and thus well yields in neighboring wells.

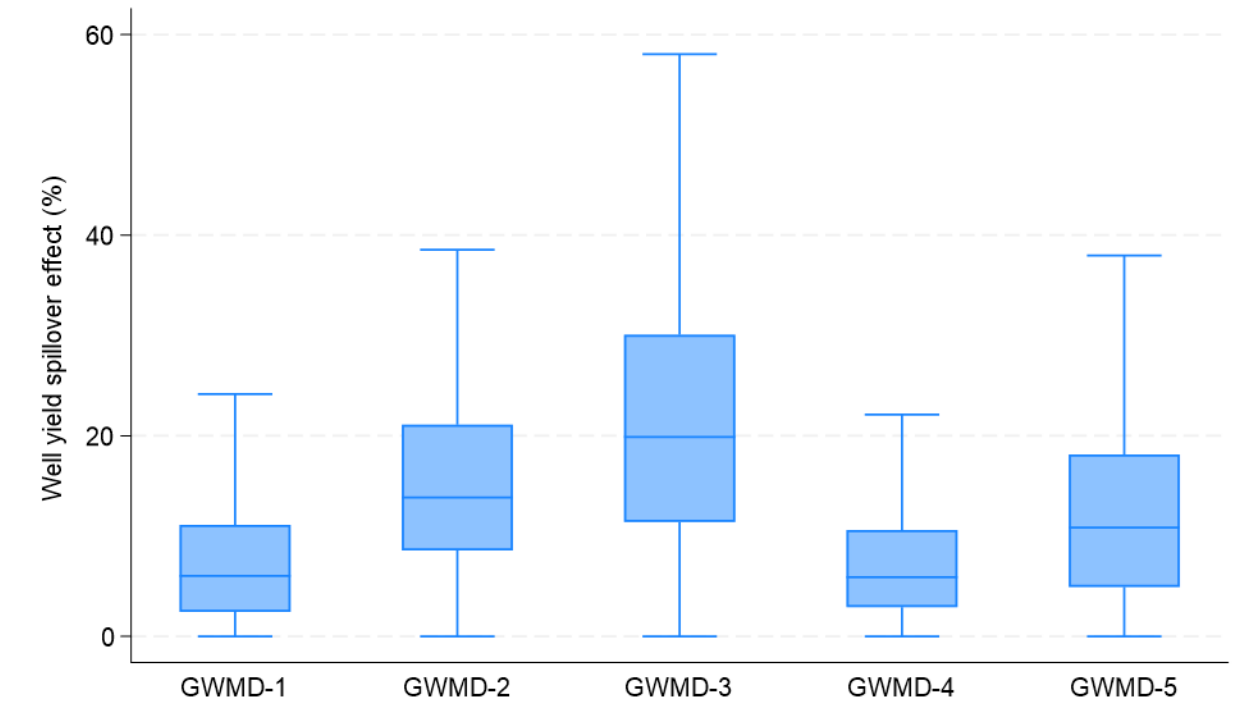
Table 4.1. Average well yields by GWMD

	Well yield without neighbors 1991	Well yield with neighbors 1991	Well yield without neighbors 2014	Well yield with neighbors 2014
GWMD-1	505 (413)	444 (350)	334 (288)	298 (247)
GWMD-2	709 (325)	594 (259)	631 (371)	525 (299)
GWMD-3	948 (457)	716 (397)	648 (413)	508 (356)
GWMD-4	603 (359)	573 (692)	453 (296)	441 (657)
GWMD-5	703 (323)	612 (277)	662 (311)	573 (265)
Total	782 (430)	638 (426)	605 (372)	506 (381)

Standard deviation in parentheses

Figure 4.1 indicates that the well yield spillover effect is most prominent in GWMD-3 with median effect on well yield of 20%. The median spillover effect was 14% in GWMD-2, and 11% in GWMD-5. This spillover was least prominent in GWMD-1 and GWMD-4 with median value of 6% each.

Figure 4.1. Well yield spillover effect by GWMD



The difference in well yield spillover effects across GWMDs can be explained in terms of differences in transmissivity (Figure 4.2) and well density (Figure 4.3). Transmissivity is a measure of how easily water flows through entire saturated thickness of an aquifer. It is the combined effect of hydraulic conductivity and saturated thickness. Transmissivity determines how far the cone of depression spreads. In other words, transmissivity dictates the radius of influence of each pumping well. The larger the transmissivity, the larger the radius of influence of a given pumping well. When multiple wells operate near each other their cones of depression overlap causing well interference. Transmissivity determines how severe this interference is.

GWMD-3 has the highest median transmissivity ($12,242 \text{ ft}^2/\text{day}$) and highest interference (20%). GWMD-1 has the least transmissivity ($3,141 \text{ ft}^2/\text{day}$) and least interference (6%). This suggests that in more permeable portions of the aquifer, pumping from one well more significantly affects neighboring wells. Conditional on transmissivity, well density also affects well interference. GWMD-4 has the smallest well density and low interference (6%) but its median transmissivity ($6,735 \text{ ft}^2/\text{day}$) is similar to GWMD-5 ($6,510 \text{ ft}^2/\text{day}$) which has higher well density and higher interference (11%). Similarly, the median number of neighboring wells is 5 in both GWMDs 1 and 2, however, interference is much higher in GWMD-2 (14% vs. 6%) due to higher transmissivity.

Figure 4.2. Transmissivity by GWMD

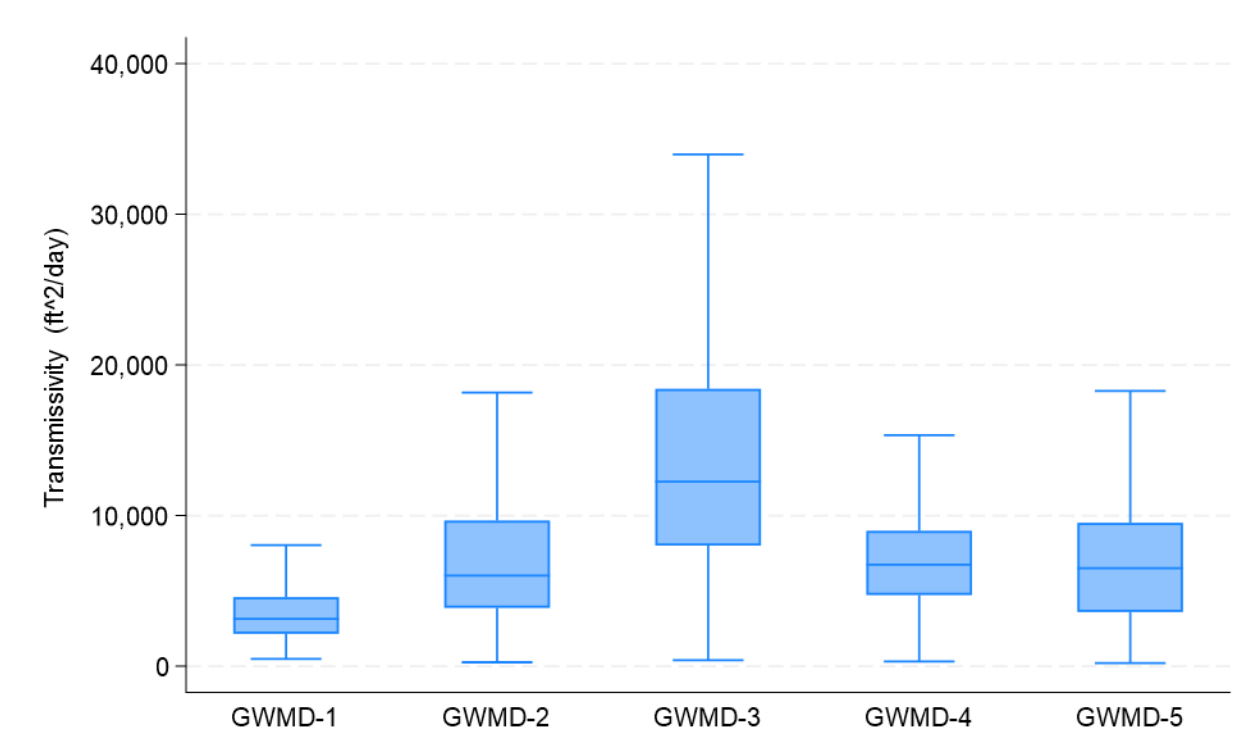
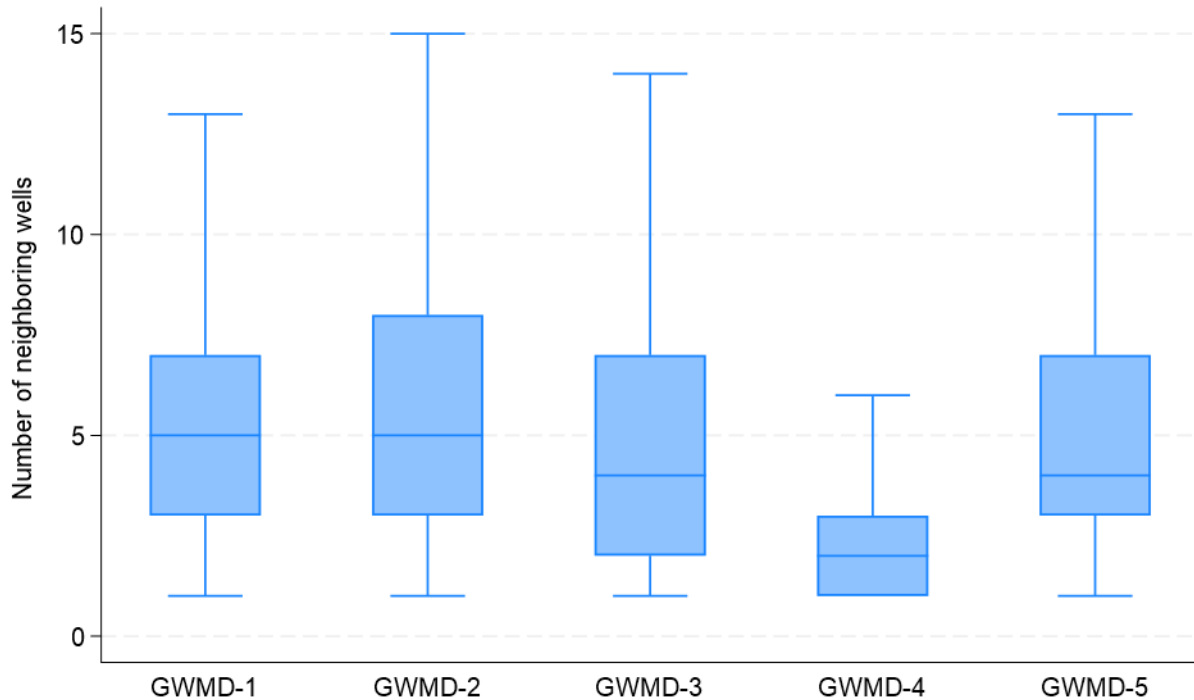
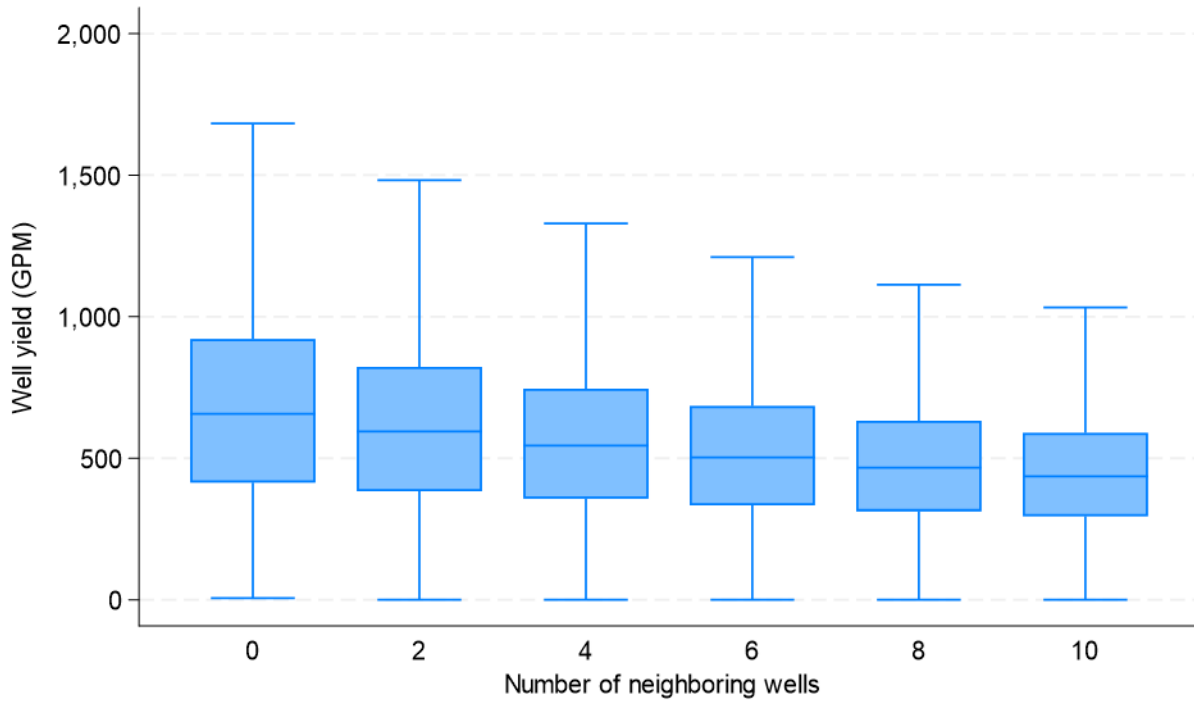


Figure 4.3. Number of neighboring wells by GWMD



To further understand the effect of well density on well yield spillover effect, we calculated well yields under multiple counterfactual scenarios by assuming 0, 2, 4, 6, 8, and 10 neighbors, each located at 0.5 mile distance from each target well. The median number of actual neighbors in our data was 4 with 95% of the wells having between 0 and 10 neighbors. Figure 4.4 depicts the inverse relationship between well yields and number of neighbors. The well yield decreases as the number of neighbors increases. In the scenario when there are no neighbors, the median well yield is the highest (656 GPM). As the number of neighboring wells increases to 10, the median well yield drops to 436 GPM, a 34% decrease. This is in line with the theory of well interference, whereby competition between wells for the same water reduces individual productivity of each well.

Figure 4.4. Relationship between well yield and number of neighbors



4.4 Average effect of neighbors on water use

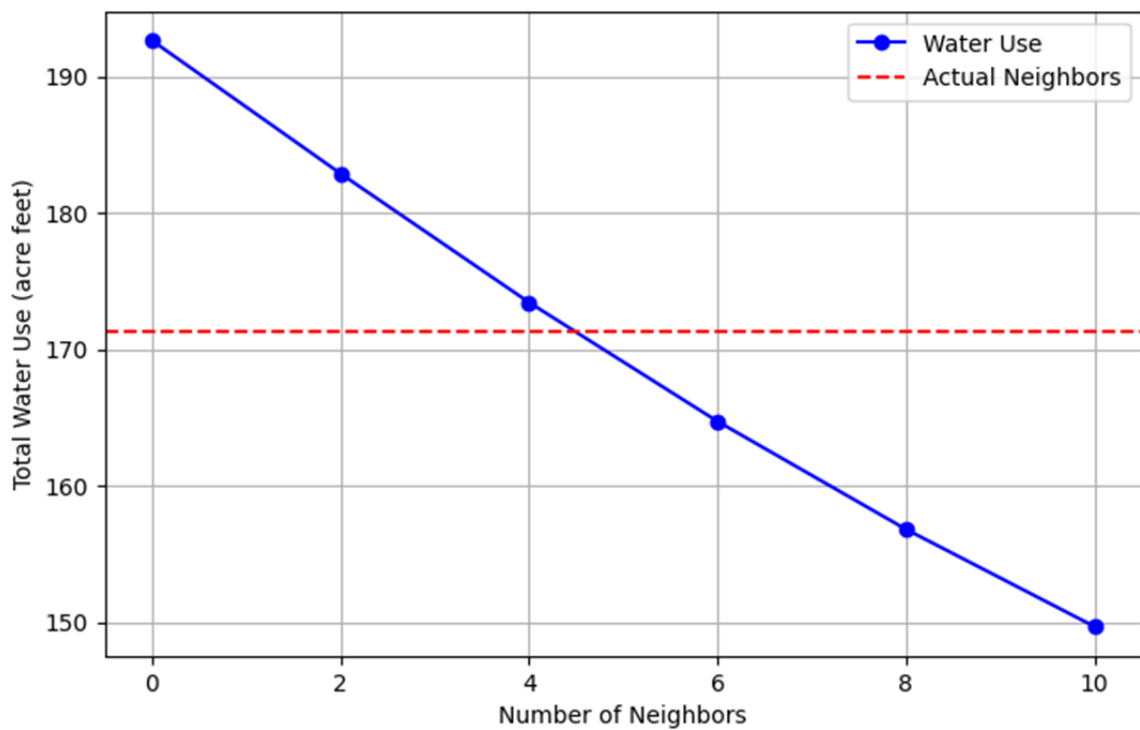
In the previous section we observed the significant inverse relationship between well density and the well yield. Here we explore how reduced well yield due to higher well density affects water use by the farmers. To answer this, we predict the water use under multiple counterfactual scenarios of different well densities using estimates from econometric models presented in Chapter 3. Specifically, we used econometric models (3.9-3.11) to predict the irrigated acres, probability of crop choice and water application depth for each crop using well yields under counterfactual scenarios described in the previous section. The predicted water use for each scenario was estimated as follows:

$$\widehat{W}(y) = \widehat{A}(y) \sum_{j=1}^J \widehat{S}_j(y) \widehat{W}_j(y), \quad (4.2)$$

where $\widehat{W}(y)$ denotes total predicted water use, $\hat{A}(y)$ denotes predicted irrigated acres, $\hat{S}_j(y)$ denotes predicted probability for each of the possible $j = 1, \dots, 4$ crops and $\widehat{W}_j(y)$ denotes predicted water application depth for each crop j .

Figure 4.5 illustrates the relationship between total water use and number of neighbors. As the number of neighbors increases, total water use decreases. Total water use decreases by 22.3% (from 192.62 to 149.67 acre-feet) when moving from no neighbors to 10 neighbors. Total water use decreases by 11.1% (from 192.62 to 171.33 acre-feet) when compared between no neighbors and actual neighbors.

Figure 4.5. Relationship between total water use and number of neighbors

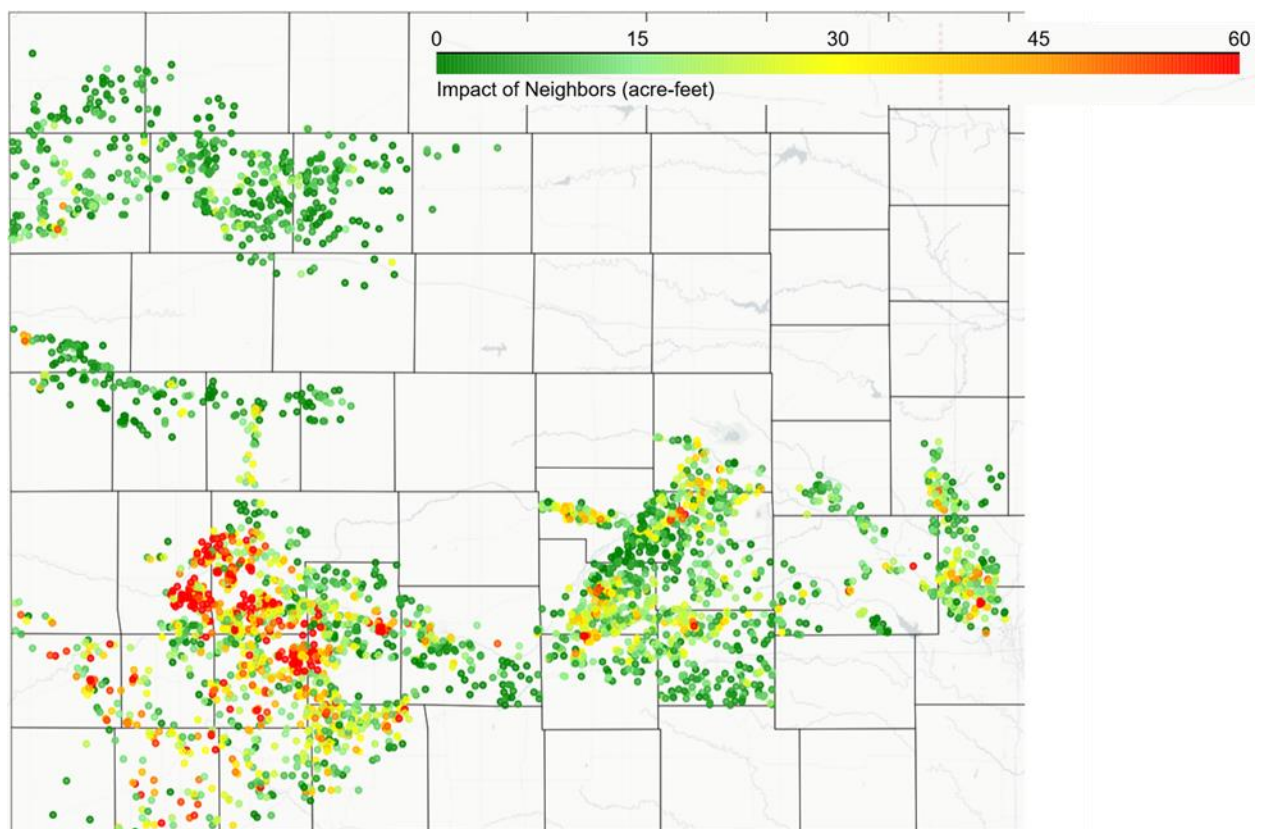


The intuition behind this effect is that as higher well density reduces well yields of individual farmers, their ability to deliver water during critical stages of crop growth and hot dry spells diminishes. This could lead to stress-induced crop yield losses and higher risk of crop failure during droughts. Since farmers with low well yields cannot meet optimal irrigation

schedule and guarantee reliable water delivery, they reduce irrigation by concentrating limited water to fewer irrigated acres and choosing less water intensive crops to avoid losses. Lower water use implicitly means lower net benefits for the farm. Apart from adapting to higher uncertainty arising from lower well yields, farmers also consider profitability of irrigation when pumping the same volume of water requires longer runtime and higher energy cost (Burness & Brill, 2001).

Figure 4.6 presents the impact of neighbors on total water use measured as difference of total water use with no neighbors and that with actual neighbors. The impact of neighbors is most pronounced in GWMD 3. This is because the transmissivity is the highest in this area. High transmissivity accelerates the well interference effect because water moves more easily meaning pumping from one well quickly and significantly impacts neighboring wells.

Figure 4.6. Impact of neighbors on total water use

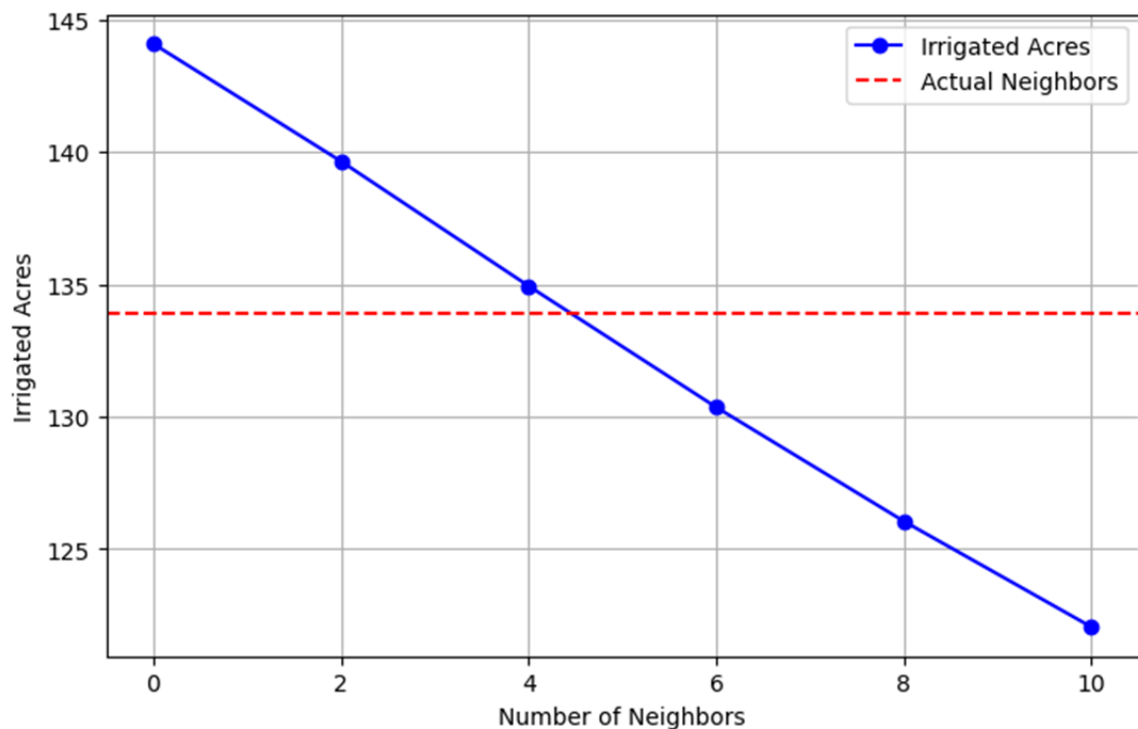


In the following sections we present a decomposition of the effect on total water use on extensive and intensive irrigation margins.

4.4.1 Extensive margin effect

Figure 4.7 illustrates the relationship between irrigated acres and the number of neighbors. As the number of neighbors increases, irrigated acres decrease. Irrigated acres decrease by 15.3% (from 144.09 to 122.05 acres) when moving from no neighbors to 10 neighbors. Similarly, irrigated acres decrease by 7.1% (from 144.09 to 133.89 acres) when compared between no neighbors and actual neighbors.

Figure 4.7. Relationship between irrigated acres and number of neighbors

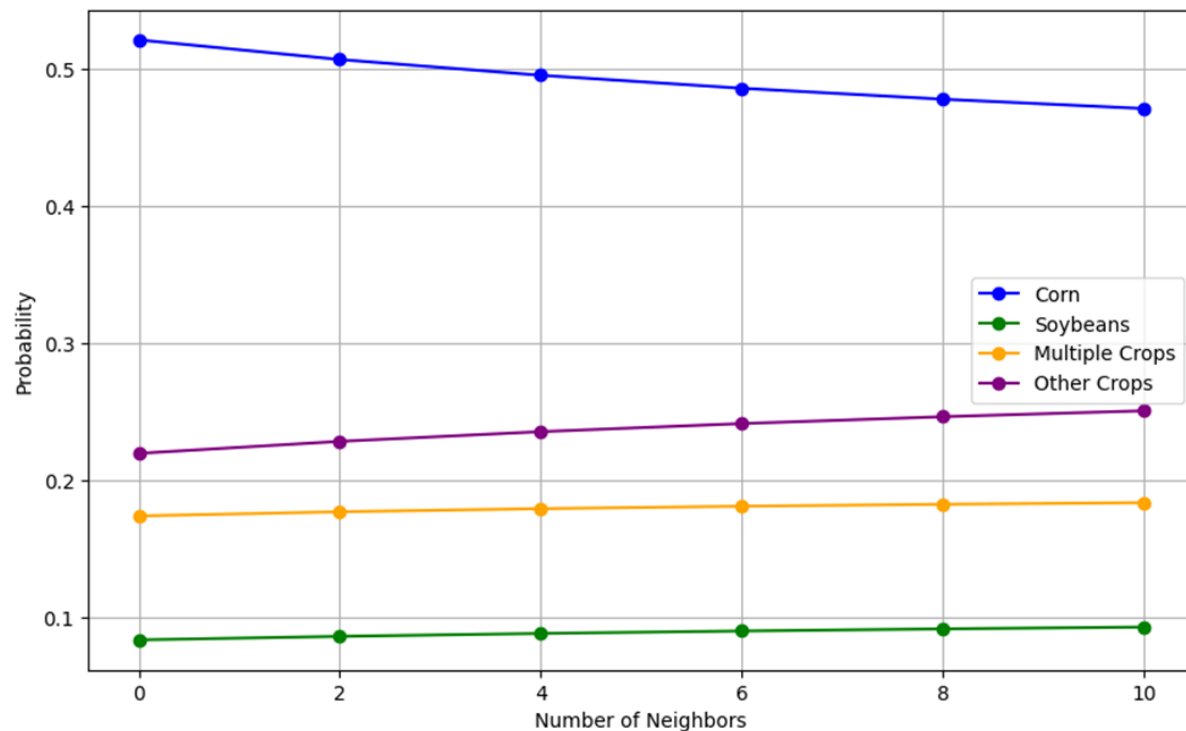


4.4.2 Indirect intensive margin effect

Figure 4.8 illustrates the relationship between the probability of growing each crop and the number of neighbors. As the number of neighbors increases, the probability of growing corn decreases, and the probability of growing other crops increases. Specifically, the probability of

growing corn decreases by 5 percentage points (from 52.14% to 47.13%) when moving from no neighbors to 10 neighbors. Similarly, the probability of growing corn decreases by 2.62 percentage points (from 52.14% to 49.52%) when compared between no neighbors and actual neighbors scenarios. We observe slight increases in the probabilities of soybeans, multiple crops and other crops as the number of neighbors increases.

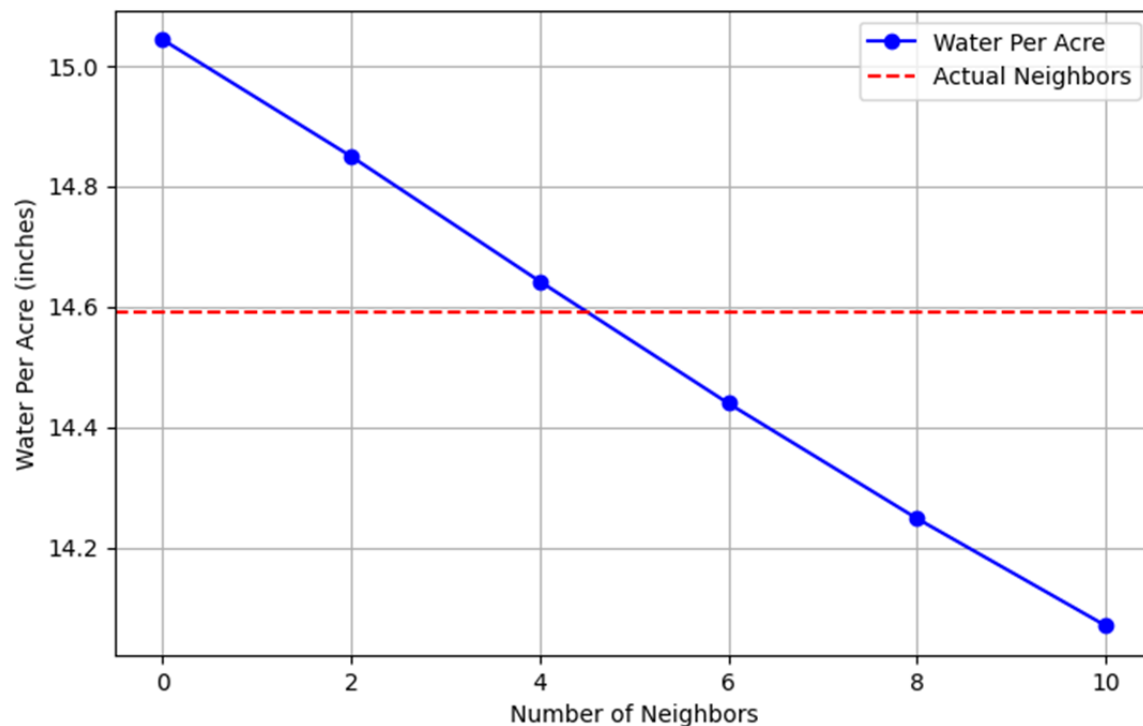
Figure 4.8. Relationship between probability of growing crops and number of neighbors



4.4.3 Direct intensive margin effect

Figure 4.9 indicates the inverse relationship between the water application depth and the well density. Water application depth decreases by 6.5% (from 15.04 inches to 14.07 inches) when moving from no neighbors to 10 neighbors. Similarly, water application depth decreases by 3% (from 15.04 inches to 14.59 inches) when compared between no neighbors and actual neighbors scenarios.

Figure 4.9. Relationship between water application depth and number of neighbors



4.5 Impact of transmissivity on well interference and water use

As described in sections 2.2 and 4.3, Transmissivity (T) defined as the product of hydraulic conductivity (K) and saturated thickness (b) governs an aquifer's capacity to supply water to wells. It directly controls a well's drawdown and radius of influence. Large T means an aquifer can deliver more water for the same drawdown thus leading to higher well yields. However, large T also means a wider cone of depression and extends well interference zone farther (Kasenow, 2001). Therefore, T can simultaneously have two conflicting effects on water use: (1) increase in water use due to higher well yield and (2) decrease in water use due to larger well interference.

To better understand the influence of T on well interference and water use, we simulated well yields under multiple counterfactual scenarios by varying hydraulic conductivity (K) and saturated thickness (b). We examined how these changes affected well yields, total water use,

and spillover effects. Specifically, we first estimated well yields in the absence of neighboring wells by varying hydraulic conductivity ($K = 25 \text{ ft/day}$, 50 ft/day , 75 ft/day , 100 ft/day , 125 ft/day), while holding all other parameters constant. The median hydraulic conductivity in our data was 97 ft/day with values ranging from 20 ft/day to 120 ft/day . Water use was then predicted using econometric models (equations 3.9–3.11). Subsequently, we re-estimated well yields assuming the presence of four neighboring wells (the median of actual neighbors), each located 0.5 miles from the target well, and again predicted water use.

We defined well yield spillover as the percentage change in well yield due to the presence of neighboring wells, relative to the no-neighbors scenario. Similarly, water use spillover was calculated as the percentage change in water use between the neighbors and no-neighbors scenarios. This analysis was repeated by varying saturated thickness ($b = 50 \text{ ft}$, 75 ft , 100 ft , 125 ft , 150 ft), with all other variables held constant, to evaluate the resulting changes in well yield, water use, and their respective spillovers. The median saturated thickness in our data was 94 ft with majority of the data ranging between 50 ft and 150 ft .

4.5.1 Impact of hydraulic conductivity

Figure 4.10 (a) illustrates the direct relationship between well yield and K . As K increases from 25 ft/day to 125 ft/day average well yield with four neighbors increases from 210 GPM to 793 GPM and the well yield without neighbors increases from 227 GPM to 1024 GPM. This is in line with the theory; for a given aquifer thickness, higher K yields higher transmissivity, directly raising well yield. Additionally, the gap between well yield without neighbors and well yield with four neighbors widens with increasing K .

Figure 4.10. Impact of hydraulic conductivity on well yield, water use and spillover

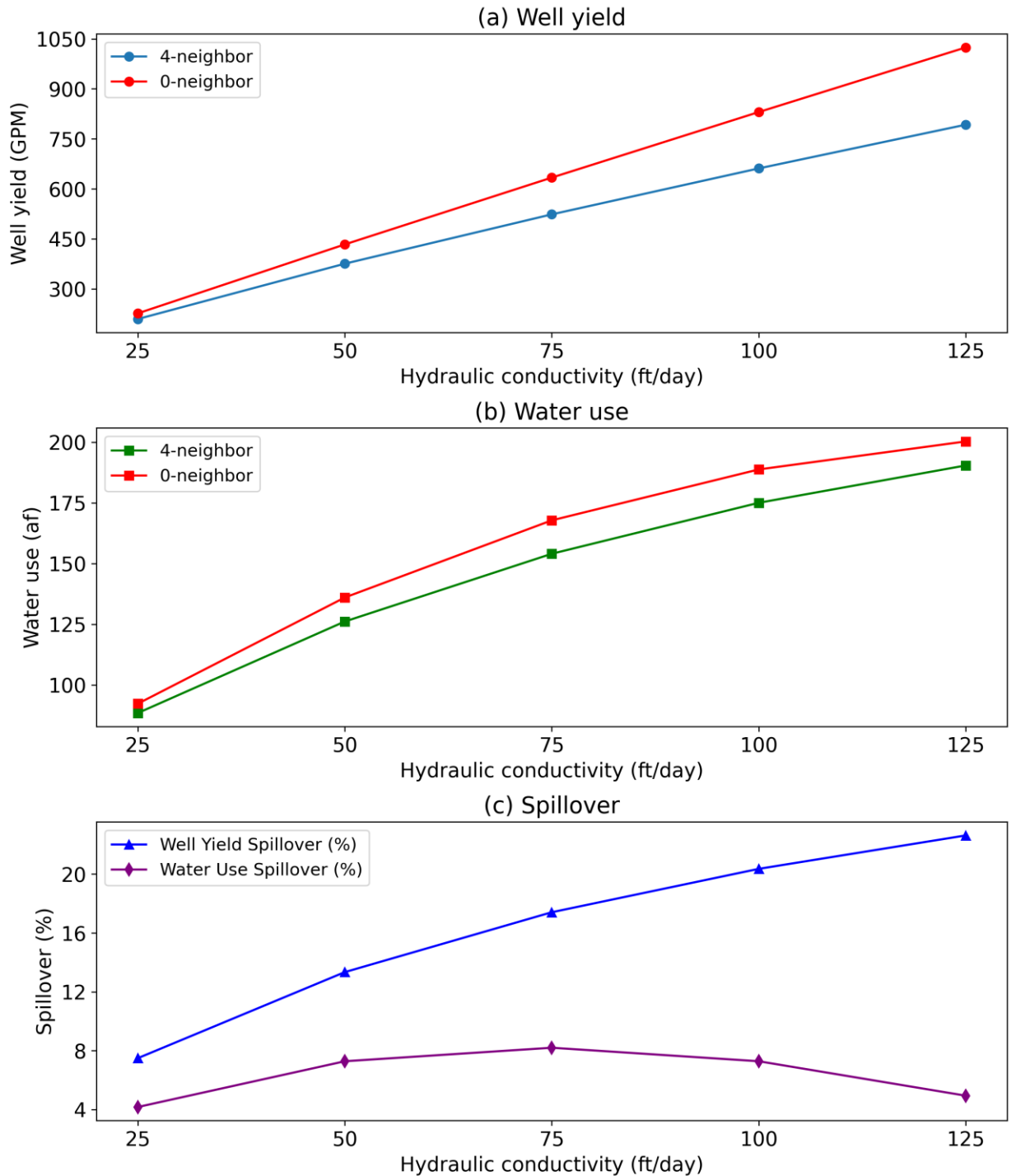


Figure 4.10 (b) illustrates that for a given K, adding neighbors reduces water use. At $K=25$ ft/day, going from no neighbors to four neighbors reduces water use by 3.85 af (from

92.26 *af* to 88.42 *af*). Similarly, at $K=125 \text{ ft/day}$, neighbors reduce water use by 9.9 *af* (from 200.31 *af* to 190.41 *af*). Additionally, keeping the number of neighbors constant, an increase in K leads to increased water use. Increasing K from $K=25 \text{ ft/day}$ to $K=125 \text{ ft/day}$ with four neighbors raises water use by 102 *af* (from 88.42 *af* to 190.41 *af*). Therefore, the increase in well yield due to higher K has the dominant impact on water use than the decrease in well yield due to well interference.

Figure 4.10 (c) illustrates the relationship between spillover and K . The water use spillover graph lies below well yield spillover graph indicating that well interference reduces well yield more than it reduces water use. Alternatively, only a fraction of well yield loss due to interference is translated into water use reduction. Additionally, with the increase in K the gap between well yield spillover and water use spillover widens from 3.3 percentage points at $K=25 \text{ ft/day}$ to 17.7 percentage points at $K=125 \text{ ft/day}$.

Well yield spillover increases with K , however, this increase becomes smaller at higher levels of K , showing a diminishing marginal increase. As K increases from 25 ft/day to 50 ft/day well yield spillover rises by 5.85 percentage points (from 7.49% to 13.34%). In contrast, an increase in K from 100 ft/day to 125 ft/day yields a much smaller increase in well yield spillover of only 2.27 percentage points (from 20.36% to 22.63%).

Water use spillover increases with K up to $K=75 \text{ ft/day}$ after which it declines. Specifically, as K increases from 25 ft/day to 75 ft/day water use spillover increases by 4.03 percentage points (from 4.17% to 8.20%). In contrast, as K increases from 75 ft/day to 125 ft/day water use spillover decreases by 3.26 percentage points (from 8.20% to 4.94%).

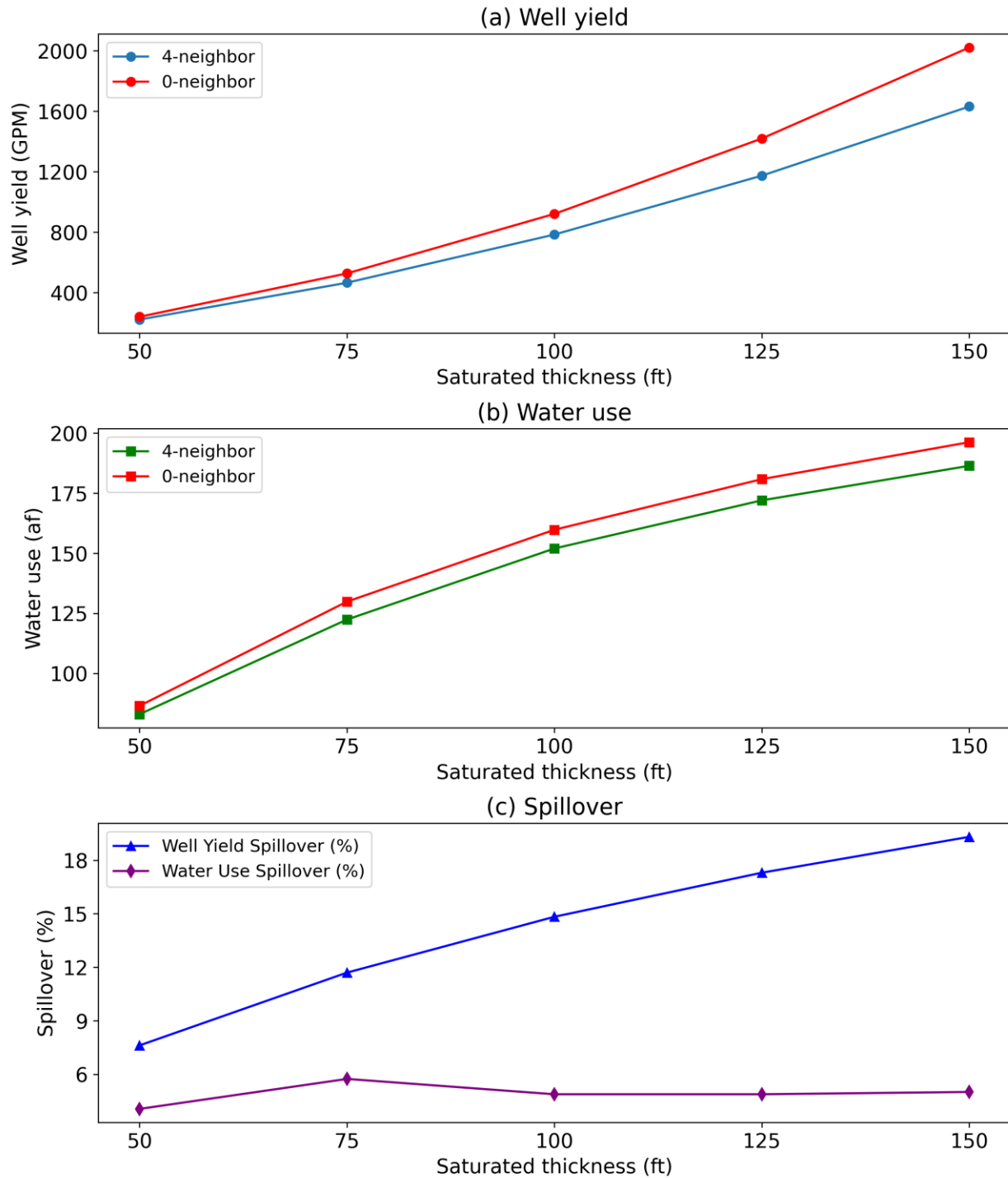
4.5.2 Impact of saturated thickness

Figure 4.11 (a) illustrates the direct relationship between well yield and saturated thickness (b). A large b at a given K means each well can withdraw more water with less drawdown but cones of depression extend farther for the same drawdown (Kasenow, 2001). The graph for well yield with no neighbors lies above the graph for well yield with four neighbors and the gap between the two widens as b increases.

Figure 4.11 (b) illustrates that for a given b adding neighbors reduces water use. At $b=50$ *ft*, going from no neighbors to four neighbors reduces water use by 3.51 *af* (from 86.53 *af* to 83.02 *af*). Similarly, at $b=150$ *ft*, neighbors reduce water use by 9.83 *af* (from 196.25 *af* to 186.41 *af*). Additionally, keeping the number of neighbors constant, an increase in b leads to a substantial increase in water use. Increasing b from 50 *ft* to 150 *ft* with four neighbors raises water use by 103.39 *af* (from 83.02 *af* to 186.41 *af*). Therefore, an increase in well yield due to higher b has a dominant impact on water use than a decrease in well yield due to well interference.

Figure 4.11 (c) illustrates the relationship between spillover and b . Water use spillover lies below the well yield spillover. The well yield spillover increases significantly with b . As b increases, well interference increases due to wider cones of depression. Water use spillover fluctuates slightly but shows no strong increasing trend. There is a peak at $b=75$ *ft*, but overall water use spillover remains relatively moderate and fluctuates between 4% and 5.74%.

Figure 4.11. Impact of saturated thickness on well yield, water use and spillover



Chapter 5 - Conclusion

This study pursued three objectives: (1) estimate well yields and analyze their spatial and temporal variation across the High Plains Aquifer region of Kansas, (2) empirically evaluate farmers' irrigation response to limited well yields along extensive margin (irrigated acreage), indirect intensive margin (crop choice) and direct intensive margin (water application depth per acre), (3) estimate well yield spillover effects resulting from interference among neighboring wells and discuss how these translate into changes in water use at the farm level.

The spatiotemporal analysis of well yields across the High Plains Aquifer region of Kansas from 1991 to 2014 reveals substantial decline in average well yields that is most pronounced in GWMD-1 (33% decrease), GWMD-3 (29% decrease) and GWMD-4 (23% decrease), compared to relatively stable conditions in GWMD-2 and GWMD-5. The driving force behind the change in well yield overtime is the change in saturated thickness.

The empirical analysis reveals that well yield is a critical determinant of water use at farm level. On average a 100 GPM decrease in well yield is associated with 13.5 acres decrease in irrigated area, 0.47 inches decrease in water application depth, and 3 percentage points decrease in the probability of growing corn. There is a non-linear relationship between well yield and water use whereby water use response is most pronounced at low to moderate well yields (250-750 GPM). The elasticity decomposition results reveal that three-quarters of the water use adjustment occurs at the extensive margin, highlighting acreage response as farmers' primary adaptation mechanism. At 1250 GPM well yield ceases to be a binding constraint, and the water use is dictated by land and water availability constraints. Decrease in water use at low well yields highlights how farmers trade profitability for risk reduction. The strongest irrigation responsiveness occurs at low to moderate well yields where flexibility to meet crop water

demand at optimal time is the binding constraint. Policies targeting efficiency improvements in these areas would enable farmers to expand production and choose more profitable crops, avoiding overinvestment in high well yield areas.

Furthermore, we quantify how transmissivity and well density jointly determine well yield reductions. Our findings demonstrate that well interference creates significant spillover effects that vary substantially across hydrological settings. The median spillover effects range from 6% in low transmissivity areas (GWMD-1) to 20% in high transmissivity areas (GWMD-3). Similarly, we find that identical well densities produce different spillover effects across geological formations. These effects have real agricultural consequences. Counterfactual simulations demonstrate that high well density (10 neighbors) can decrease water use by 22.3% compared to isolated wells, as well interference constrains farmers' ability to meet peak crop water demands. These findings suggest that groundwater management strategies should account for spatial variation in transmissivity when determining optimal well spacing. Additionally, future groundwater governance could benefit from spatially explicit regulations that account for hydrological constraints revealed by these well interference effects.

Our study establishes empirical evidence on how limited well yields and well interference affect optimal water use. It also establishes empirical evidence that impact of well yields extends beyond decisions about water use to also influence decisions about irrigation technology adoption. Specifically, we find that at low to medium well yields the instantaneous probability of transitioning from flood irrigation system to center pivot irrigation system increases with well yield up to 750 GPM. This probability declines at well yields higher than 750 GPM. We find no significant impact of well yield on transition from standard center pivot irrigation system to center pivot with low drop nozzles.

Empirical evidence on how limited well yields affect agricultural land values remains scarce. Future studies could investigate how limited well yields and well interference influence agricultural land values. Another avenue for further research pertains to how knowledge about spatially explicit nature of well yield spillover effect could be used to design market based mechanisms where water rights could be traded among senior and junior water right holders. A key limitation of our study is the omission of strategic pumping behavior where farmers may increase current period extraction to preempt reduced future access due to neighbors' water use.

An additional area of inquiry involves examining how limited well yields and well interference influence participation in groundwater right retirement programs aimed at water conservation. Lower well yields coupled with significant interference from neighboring wells may decrease the opportunity cost of enrolling in water right retirement programs. Specifically, farmers with higher well yields can reliably meet crop water demand during the entire growing season leading to greater expected net benefits from irrigation and thus lower likelihood of well retirement. On the other hand, significant well interference reduces effective well yields thereby increasing the propensity to retire wells among affected farmers.

This phenomenon may have two key implications for water conservation. First, since wells in areas with low well yields and greater interference are more likely to enroll, the total water conserved may be less than desired levels. Second, while retiring wells in high interference areas may mitigate spillover effects among neighboring wells, the remaining wells could compensate by increasing pumping, potentially offsetting conservation gains. Future research should explore these behavioral dimensions in groundwater management strategies.

Another key limitation of our study is the assumption of risk neutral behavior of farmers in our conceptual model. In reality, aquifer depletion undermines irrigation's effectiveness to

buffer against climate induced stress. Specifically, declining well yields diminish farmers' ability to meet crop water demand during critical growth stages and buffer against extreme heat and drought, thereby increasing crop yield variability. In response, farmers may turn to crop insurance as a safety net against crop yield shortfalls. As declining well yields increase the probability of crop shortfall, insurers may adjust premiums upwards in affected areas. Future research should incorporate risk considerations into farmers' profit maximization framework and examine how declining well yields affect both demand and premium rates of crop insurance across irrigated farms.

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Appendix A Python code for estimating well yields

```
# Install Pyomo and other necessary libraries

!wget -q https://repo.anaconda.com/miniconda/Miniconda3-latest-Linux-x86_64.sh
!chmod +x Miniconda3-latest-Linux-x86_64.sh
!./Miniconda3-latest-Linux-x86_64.sh -b -f -p /usr/local
import sys
sys.path.append('/usr/local/lib/python3.10/site-packages')
!conda install -c conda-forge ipopt -y
!apt-get install -y -qq coinor-ipopt
!pip install pyomo
!pip install openpyxl # Required for Excel export

# Import libraries
import numpy as np
import pandas as pd
from pyomo.environ import *

# Load data from CSV files (replace with your file paths)
# Ensure the CSV files are uploaded to Google Colab
neighbors_data = pd.read_csv('neighbors.csv') # Replace with your file name
indata = pd.read_csv('indata.csv') # Replace with your file name

# Define sets
num_wells = 50960
num_groups = 5096
i = range(1, num_wells + 1) # Wells
j = ['stk', 'hyd', 'trns', 'sy', 'days', 'r'] # Well parameters (excluding 'dist')
g = range(1, num_groups + 1) # Groups
```

```

# Define parameters
# Load 'dist' from neighbors.csv
c = {(row['g'], row['i']): row['dist'] for _, row in neighbors_data.iterrows()} # Neighbors data
(distance)

# Load other parameters from indata.csv
cd = {row['g']: {param: row[param] for param in j} for _, row in indata.iterrows()} # Well
parameters

# Extract specific parameters
stk = {g: cd[g]['stk'] for g in g}
hyd = {g: cd[g]['hyd'] for g in g}
trns = {g: cd[g]['trns'] for g in g}
sy = {g: cd[g]['sy'] for g in g}
days = {g: cd[g]['days'] for g in g}
r = {g: cd[g]['r'] for g in g}
pi = 3.142857 # Value of pi

# Define batch size
batch_size = 100 # Number of groups per batch
num_batches = (num_groups + batch_size - 1) // batch_size # Total number of batches

# Initialize a dictionary to store pumping rates
pumping_rates = {}

# Process each batch sequentially
for batch in range(num_batches):
    print(f'Processing batch {batch + 1} of {num_batches}...')

    # Define the range of groups for this batch

```

```

start = batch * batch_size + 1
end = min((batch + 1) * batch_size, num_groups)
batch_groups = range(start, end + 1)

# Define the model for this batch
model = ConcreteModel()

# Define variables for this batch
model.z = Var(within=Reals) # Objective variable
model.saqu = Var(batch_groups, within=NonNegativeReals) # Drawdown due to pumping in
the target well
model.u = Var(batch_groups, i, within=Reals) # Parameter for Sneighbor
model.sneighbor = Var(batch_groups, i, within=Reals) # Drawdown due to pumping in
neighboring well
model.sum_sneighbor = Var(batch_groups, within=Reals) # Sum of drawdown due to
neighboring wells
model.sall = Var(batch_groups, within=Reals) # Total drawdown (Saqu + Sneighbor)
model.pump = Var(batch_groups, within=NonNegativeReals) # Pumping rate

# Define objective function for this batch
model.obj = Objective(expr=sum(model.pump[g] for g in batch_groups), sense=maximize)

# Define constraints for this batch
def eq_Saqu_rule(model, g):
    return model.saqu[g] == (model.pump[g] * 192.5) / (4 * pi * trns[g]) * (
        -0.5772 - log((r[g] ** 2 * sy[g]) / (4 * trns[g] * days[g])))
model.eq_Saqu = Constraint(batch_groups, rule=eq_Saqu_rule)

def eq_u_rule(model, g, i):
    if g != i and c.get((g, i), 0) != 0:
        return model.u[g, i] == (c[g, i] ** 2 * sy[g]) / (4 * trns[g] * days[g])

```

```

else:
    return Constraint.Skip
model.eq_u = Constraint(batch_groups, i, rule=eq_u_rule)

def eq_Sneighbor_rule(model, g, i):
    if g != i and c.get((g, i), 0) != 0:
        u = model.u[g, i]
        return model.sneighbor[g, i] == (
            -0.5772 - log(u + 0.00001) + u - 0.25 * u ** 2 + 0.05556 * u ** 3 - 0.01042 * u ** 4 +
            \
            0.001667 * u ** 5 - 0.000231481481481481 * u ** 6 + 0.000028344671202 * u ** 7 -
            \
            0.000003100198413 * u ** 8 + 0.000000306192436 * u ** 9) * (model.pump[g] *
            192.5) / (4 * pi * trns[g])
    else:
        return Constraint.Skip
model.eq_Sneighbor = Constraint(batch_groups, i, rule=eq_Sneighbor_rule)

def eq_Sneighbor_sum_rule(model, g):
    return model.sum_sneighbor[g] == sum(model.sneighbor[g, i] for i in i if g != i and c.get((g,
i), 0) != 0)
model.eq_Sneighbor_sum = Constraint(batch_groups, rule=eq_Sneighbor_sum_rule)

def eq_Sall_rule(model, g):
    return model.sall[g] == model.saqu[g] + model.sum_sneighbor[g]
model.eq_Sall = Constraint(batch_groups, rule=eq_Sall_rule)

def eq_constraint_rule(model, g):
    return model.sall[g] <= stk[g] / 3
model.eq_constraint = Constraint(batch_groups, rule=eq_constraint_rule)

```

```

# Solve the model for this batch
solver = SolverFactory('ipopt') # Use IPOPT solver for NLP
results = solver.solve(model, tee=True)

# Save pumping rates for this batch
for g in batch_groups:
    pumping_rates[g] = model.pump[g].value

# Combine results into a DataFrame
pumping_rates_df = pd.DataFrame(list(pumping_rates.items()), columns=['Group', 'Pumping
Rate'])

# Save pumping rates to an Excel file
output_file = 'pumping_rates.xlsx'
pumping_rates_df.to_excel(output_file, index=False)

# Download the output file
from google.colab import files
files.download(output_file)

print(f'Pumping rates saved to {output_file}')

```