Groundwater level and crop choice: Evidence from a dynamic discrete choice model

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Abstract

This study develops a dynamic discrete choice model to estimate the impact of groundwater decline on crop choices in NM eastern High Plains. We take advantage of the recently available high-resolution remote sensing agricultural land cover data developed by the National Agricultural Statistics Service of USDA. The model considers the forward-looking behavior of farmers who face changes in groundwater level, market trends, and climate. The results show that farmers tend to respond to the decline of the groundwater level by choosing high-value crops such as winter wheat instead of switching to more drought-resistant crops like sorghum. Both winter wheat and sorghum have been grown in the region historically. Therefore, switching cost is unlikely to explain the result. On the one hand, when the groundwater resources are in decline, farmers are forced to invest more to pump the same amount of water. Choosing a high-value crop justifies such an investment decision. On the other hand, this also reflects the common-pool resource problem of groundwater extraction. As the common-pool resource shrinks, users tend to increase the rate of extraction as a result of intensifying competition. This inflates the likelihood of choosing high-value crops instead of more drought-resistant options.

***Keywords*:** Crop Choice, Dynamic Discrete Choice, High Plains Aquifer, Groundwater, Climate Change, New Mexico Agriculture

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1. Introduction

Agricultural production has often been regarded as the main driver of groundwater depletion in arid/semi-arid areas across the world (e.g. Haacker et al., 2016). Admittedly, the productivity of crop production has seen a significant increase since World War II empowered by advanced pumping and irrigation technologies (e.g. Hornbeck and Keskin, 2014). In recent decades, however, a pressing issue faced by irrigated agriculture is groundwater over-pumping that exceeds the recharge rate of many aquifers. The groundwater resources are depleting and some are at the risk of disappearing. The key challenge to groundwater management is the tragedy of the commons - the groundwater resource is over-extracted due to competition and outdated governing institutions for water (e.g. Glennon, 2004). The High Plains aquifer spanning between the US West and Midwest is a good example. Sustainable groundwater resource management is often called upon as a solution, which mainly concerns agricultural water use. Among policy recommendations, increasing the efficiency of the irrigation system and managing cropping practice are the major ones (e.g. Garcia-Vila et al., 2008; Wallander, 2017; Wang, 2019).

This study focuses on the relationship between groundwater decline and crop choice. Crop choice is considered the main adaptation strategy at the intensive margin (holding the total acreage in production given) in response to an irrigation water supply change. At the intensive margin, farmers grow high-value crops (e.g. cotton and corn) when water supply for irrigation is abundant; and switch back to drought-resistant crops (e.g. sorghum and millet) when water supply becomes constrained or expensive. Crop rotation and market prices are other important factors that can potentially influence farmers' crop choice decisions. In general, the literature has found that crop choice in irrigated regions is sensitive to water cost and water supply in the long run (e.g. Kim et al., 1989; Wu et al. 1994; Ding and Peterson 2003; Lamm et al., 2007; Kuil et al., 2018).

Understanding crop choice response is important for agricultural water management and policy-making. And it can become essential for rural communities that rely on cash receipts from crop production. As an adaptation strategy, adjusting crop choice can help to smooth income shocks due to exogenous environmental changes such as climatic variability and decline of groundwater level. Meanwhile, understanding how farmer crop choice decision-making responds to (expected, in particular) exogenous environmental changes provides valuable inputs in building drought-resistant rural communities. This study takes advantage of remote-sensing cropland data and develops a dynamic discrete choice model of crop choice at the field level. Different from conventional multinomial choice models that treat crop choice in different years as independent decisions, the proposed model explicitly accounts for historical decisions of farmers thus linking crop choice decisions across adjacent years. Including dynamics has significant impacts on the likelihood of choosing among different crops when farmers face a changing groundwater level.

2. Model

2.1. The Conceptual Model

In irrigated regions, crop production involves key input decisions concerning land use, crop choice, and irrigation water allocation. Land use change usually happens as a long-run adjustment, especially when it entails adjustments such as land conversion or switching between rainfed and irrigated land. Crop choice and irrigation water allocation, on the other hand, are short-run adjustments. Farmers evaluate their decisions on crop choice and irrigation from season to season. A major difference between the two is that irrigation water use is often constrained at the regional scale (e.g. irrigation district or watershed). Crop choice decisions happen at the field level.

This study treats each cropland field as a decision-making unit and its crop choice is decided by the operating farmer - the decision-maker. The farmer receives flow utility from income generated by crop production. We make two assumptions: (1) the farmer is a price-taker; (2) the groundwater level under the given field is exogenous to the farmer. However, the farmer has his/her own expectations about crop prices and the groundwater level derived from historical observations. Similarly, climatic information in the growing season is also exogenous to the farmer and he/she forms his/her own projections about growing season temperature and precipitation. In addition, it is important to consider crop rotation in crop choice decisions. We incorporate the crop rotation consideration into the physical state space, which will be further discussed in detail. Our analysis focuses on the impact of groundwater level on crop choice. All other factors, although important, act as control variables. Overall, farmers are forward-looking with respect to their choices and all time-varying variables that affect the value of crop production. Meanwhile, farmers are also decision-makers with a short memory - what happens in the past several years affects future decisions in a Markovian fashion.

In year t at field i, the farmer receives a location and time-specific income that depends on crop price, yield, and input costs. Given the context of our study region, the farmer's choice set is defined as: $j \in J = \{hay, corn, sorghum, wheat\}$. Ideally, we would need to compute the return of each crop choice and assume that the farmer as a rational decision-maker makes crop choice by comparing the expected returns of different crops. This particular study uses a large scale remote-sensing data set covering thousands of irrigated fields in NM High Plains. Practically, at the field level, crop yields and some of the input costs data are unavailable. In the empirical modeling, we choose to focus on the key determinants of crop return given the data availability. We include crop prices, growing season temperature and precipitation (yield determinants), and groundwater level as a proxy for irrigation water cost. Similar to Moore et al. (1994), the conceptual crop-choice decision model represents a discrete choice depending on all crop prices, water cost, and climatic variables:

$$d_j = f_j(\mathbf{p}, g, \mathbf{x}, h) \tag{1}$$

where d_j is a choice variable equal to 1 if crop j is chosen and 0 otherwise. $\mathbf{p}$ is a vector of all crop prices; g is the groundwater depth at the given location reflecting the cost of pumping water; x are climatic variables at the given location, h indicates the crop grown in the last season to capture rotation effects. Given the conceptual choice model in (1), we will develop a utility maximization framework that motivates the farmer's crop choice while considering all the dynamics. First, we discuss how to compute expectations of all time-varying variables. This is more realistic than using actual observational values because crop choice decisions are made at the beginning of the growing season.

2.2. Crop Price

The crop-specific price information is usually observed at the regional level only. That is, the crop prices only vary temporally in this study. Therefore, an autoregressive (AR) time-series model can be used to project crop prices. Here we use an AR(1) model; for a given crop j its projected price in year t (p_t^j) is given as:

$$p_t^j = \varphi_0^j + \varphi_1^j Trend_t^j + \varphi_2^j p_{t-1}^j + \zeta_t^j \tag{2}$$

where φ_0, φ_1, and φ_2 are parameters to be estimated. $Trend_t$ is a year trend. ζ_t represents random shocks. Although more general and sophisticated time-series models can be used such as ARIMA (autoregressive integrated moving average), the idea here is that price projection is a simple process as part of farmers' decision-making. Methodologically, the AR(1) assumption also facilitates the estimation of the transition probability to be discussed.

2.3. Climatic Variables

Climatic variability is typically measured by weather realizations. In this study, we use monthly temperature and precipitation data provided through the PRISM project at Oregon State University. The PRISM data have a resolution of 4 by 4 km, hence there is sufficient spatial variation across the study region. In addition, because what matters is the climatic variability in the growing season (different by crops), the climatic variables also vary by crop choice. In other words, the climatic variables are alternative-specific variables. The monthly data is then aggregated over the growing season. This study uses the growing season average temperature (T) and average precipitation (P). Similarly, we use an AR(3) model to form annual projections of growing season temperature and precipitation plus a year trend ($Trend_t$) to capture the climate trend.

For field i in year t, the crop-specific climatic variable projections are given as:

$$T_{jit} = \alpha_{ji}^{T} + \beta_{ji0}^{T} Trend_t + \beta_{ji1}^{T} T_{ji,t-1} + \varepsilon_{jit}^{T} \tag{3}$$

$$P_{jit} = \alpha_{ji}^{P} + \beta_{ji0}^{P} Trend_t + \beta_{ji1}^{P} P_{ji,t-1} + \varepsilon_{jit}^{P} \tag{4}$$

where $\alpha_{ji} = [\alpha_{ji}^{T}, \alpha_{ji}^{P}]$ capture crop-field fixed effects, $\beta_{ji0} = [\beta_{ji0}^{T}, \beta_{ji0}^{P}]$ are parameters to be estimated. ε_{jit} represents random shocks. For crops like winter wheat (grown in NM High Plains), its growing season spans over two years. In this case, the year trend variable takes the harvest year as the climatic conditions in the second year are more important to crop yield. It is also consistent with the year of price information.

2.4. Groundwater Level

The groundwater level is regularly and irregularly measured at different well locations. For any given year, these water level measurements scatter across the study region. To generate a groundwater level map that is consistent with climatic variables and crop choice data, the raw measurements are spatially interpolated across space. Therefore, the groundwater level data varies by location and year, but not by crop. For field i in year t, its groundwater level depth can be projected by an AR(1) model:

$$g_{it} = \lambda_i + \theta_{i1} g_{i,t-1} + \eta_{it} \tag{5}$$

where λ_i are field-specific fixed effects. θ_{i1}, is a parameter to be estimated. η_{it} represents white noise. The spatial interpolation of groundwater depth will be discussed in the data section. Crop rotation variable h will be defined directly as part of the state space for the dynamic model.

2.5. A Dynamic Discrete Choice Model

In the world with uncertainty, a farmer considers the future flow utility of income from growing a given crop in the choice set. By assuming additive separability of utility over time, the farmer's lifetime utility is then the discounted sum of utility from each year. His/her decision-making objective is to maximize the utility derived from the expected lifetime income,

$$MAX_{d_t \in J} \quad \sum_{t=0}^{T} \delta^t \left[u_t(X_t, d_t) + \omega(d_t) \right] \tag{6}$$

where d_t is the farmer's crop choice in year t and δ is the discount factor. $u_t(X_t, d_t)$ is the flow utility in year t given a crop choice of d_t. X_t denotes the vector of all state variables for the farmer in year t. The state variables include crop prices, climatic variables, groundwater level, and a set of indicators capturing crop rotation. Similar to Bishop (2012), the transition of the states is assumed to be Markovian, so that X_{t+1} depends on X_t and d_t only. The transition probability of the state vector is denoted as $q(X_{t+1} \mid X_t, d_t)$.

$\omega(d_t)$ is a time-varying idiosyncratic component of utility that is assumed to follow an independent and identically distributed (*i.i.d.*) Type I extreme value distribution. Such a setup of dynamic discrete choice has been commonly adopted in the literature (e.g. Rust, 1987; Bishop, 2012; Ji et al., 2014).

2.6. State Space and Utility Function

Following Scott (2014), the state space in this paper is divided into two categories: market state and physical state. The market state is represented by crop prices that follow a Markov process by construction, given that prices are projected using an AR (1) process. Climatic variables and groundwater depth in the physical state similarly follow a Markov process by construction. The physical state also includes a set of four variables indicating what was grown on the field in year $t-1$. Table 1 below summarizes the definitions:

Table 1: Summary of state variables

State Variable	Definition	Category
p_{jt}	crop-time specific price	market state
g_{it}	groundwater depth at field i	physical state
T_{it}	average growing season temperature at field i	physical state
P_{it}	average growing season precipitation at field i	physical state
$H1_{it}$	hay grown on field i in year $t-1$	physical state
$C1_{it}$	corn grown on field i in year $t-1$	physical state
$W1_{it}$	winter wheat grown on field i in year $t-1$	physical state
$S1_{it}$	sorghum grown on field i in year $t-1$	physical state

Similar to Bishop (2012) and Ji et al. (2014), the flow utility at field i in year t, $u_{it}(X_{it}, d_{it})$, can be defined as:

$$u_{it}(X_{it},d_{it}) = \begin{cases} \gamma_{h0} + \gamma_{hp}p_{jt} + \gamma_{hg}g_{it} + \gamma_{hx}Z_{it} + \omega_{jit} & if \quad j = hay \\ \gamma_{c0} + \gamma_{cp}p_{jt} + \gamma_{cg}g_{it} + \gamma_{cx}Z_{it} + \omega_{jit} & if \quad j = corn \\ \gamma_{s0} + \gamma_{sp}p_{jt} + \gamma_{sg}g_{it} + \gamma_{sx}Z_{it} + \omega_{jit} & if \quad j = sorghum \\ \gamma_{w0} + \gamma_{wp}p_{jt} + \gamma_{wg}g_{it} + \gamma_{wx}Z_{it} + \omega_{jit} & if \quad j = wheat \\ \gamma_{o0} + \gamma_{of}F_t + \gamma_{ox}R_{it} + \omega_{jit} & if \quad j = others \end{cases} \tag{7}$$

where ω_{jit} is the time-varying idiosyncratic component of utility. Z_{it} is a vector consisting of other control variables (climatic variables and rotation indicators). Similar to crop prices, F_t is the regional average grazing fee for pasture and vacant cropland. R_{it} is a vector consisting only of rotation indicators (i.e. $Z_{it} = [T_{it}, P_{it}, R_{it}]$). Note that the category *others* includes pasture and cropland that is in fallow. The potential benefits of fallow are captured through rotation variables in R_{it}. γ_{h0}, γ_{c0}, γ_{s0}, and γ_{w0} represent fixed utility component related to growing each of the four major crops. As pointed out by Ji et al. (2014), the rotation indicators in the physical state capture possible income differences associated with different types of crop rotations. Together with the climatic variables, these control variables capture benefits and cost-saving effects related to each crop choice.

2.7. *Estimation Strategy*

The dynamic discrete choice model developed above has two essential assumptions: (1) the evolution of market states and physical states is Markovian; (2) the additive separability of flow utility. These are common assumptions in the literature to make the decision-making problem in equation (6) computationally feasible (e.g. Rust 1987; Bishop, 2012). Given these assumptions, the Bellman equation for value function can be written as:

$$V_t(X_t, \omega(d_t)) = MAX_{d_t \in J}\left[v_t(X_t, d_t) + \omega(d_t)\right] \tag{8}$$

where the value function $v_t(X_t, d_t)$ can be written as,

$$v_t(X_t,d_t) = u_t(X_t,d_t) + \delta \int \sum_{X_{t+1}} V_{t+1}(X_{t+1},\omega(d_{t+1}))q(X_{t+1} \mid X_t,d_t)dF(\omega(d_{t+1})) \tag{9}$$

or equivalently,

$$v_t(X_t,d_t) = u_t(X_t,d_t) + \delta E(V_{t+1}(X_{t+1},\omega(d_{t+1}))) \tag{10}$$

Since $\omega(d_t)$ follows an $i.i.d$ Type I extreme value distribution, replace the second term on the right hand side of (9) and (10) with Logit inclusive value, which gives:

$$v_t(X_t,d_t) = u_t(X_t,d_t) + \delta \sum_{X_{t+1}} ln\left[\sum_{j=1}^{J} exp\left(v_{t+1}(X_{t+1},d_{t+1}=j)\right)\right] q(X_{t+1} \mid X_t,d_t) \tag{11}$$

This is a recursive equation which makes its estimation computationally difficult. Following Hotz and Miller (1993), Arcidiacono and Miller (2011), and Bishop (2012), it can be shown that,

$$
\begin{aligned}
v_t(X_t, d_t = j^{(t)}) = u_t(X_t, d_t = j^{(t)}) \\
&+ \delta \sum_{X_{t+1}} ln\left[Pr(d_{t+1} = j^{(t+1)} \mid X_{t+1})^{-1}\right] \times q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta \sum_{X_{t+1}} \left[u_{t+1}(X_{t+1}, d_{t+1} = j^{(t+1)})\right] \times q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} ln\left[Pr(d_{t+2} = j^{(t+2)} \mid X_{t+2})^{-1}\right] \\
&\times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} \left[u_{t+2}(X_{t+2}, d_{t+2} = j^{(t+2)})\right] \\
&\times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^3 \sum_{X_{t+1}} \sum_{X_{t+2}} \sum_{X_{t+3}} ln\left[Pr(d_{t+3} = j^{(t+3)} \mid X_{t+3})^{-1}\right] \\
&\times q(X_{t+3} \mid X_{t+2}, d_{t+2} = j^{(t+2)}) \times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^3 \sum_{X_{t+1}} \sum_{X_{t+2}} \sum_{X_{t+3}} \left[u_{t+3}(X_{t+3}, d_{t+3} = j^{(t+3)})\right] \\
&\times q(X_{t+3} \mid X_{t+2}, d_{t+2} = j^{(t+2)}) \times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = j^{(t)})
\end{aligned}
$$

where $Pr(\cdot)$ is the conditional choice probability, which can be estimated in a preliminary step. $j^{(t)}$, $j^{(t+1)}$, $j^{(t+2)}$, and $j^{(t+3)}$ represent crop choices made in year t, $t+1$, $t+2$, and $t+3$, respectively. Given the Logit framework, the conditional choice probability is defined as,

$$
\begin{aligned}
P(d_t = j^{(t)} \mid X_t) &= \frac{exp\left(v_t(X_t, d_t = j^{(t)})\right)}{\sum_j exp\left(v_t(X_t, d_t = j)\right)} \\
&= \frac{1}{\sum_j exp\left(v_t(X_t, d_t = j) - v_t(X_t, d_t = j^{(t)})\right)}
\end{aligned}
$$

An estimate of $P(d_t = j^{(t)} \mid X_t)$, say $\hat{P}(d_t = j^{(t)} \mid X_t)$, can be used to replace the conditional choice probability in value function $v_t(X_t, d_t = j^{(t)})$. Similarly, all transition probabilities $q(\cdot)$ can also be replaced with empirical estimates in a preliminary step using historical observations. The above lengthy value function $v_t(X_t, d_t = j^{(t)})$ can be further simplified using the fact that all state variables are Markovian. Given that the farmer only has one period of memory, therefore the state dependence breaks after two periods. In the value function, regardless of the choice made in year t, the farmer will be indifferent on the current value of the choice he or she will make in year $t+3$. That is, given two different current period choices, say $j^{(t)} = a$ and $j^{(t)} = b$, we have,

$$
\begin{aligned}
v_t(X_t, d_t = a) - v_t(X_t, d_t = b) & \\
&= u_t(X_t, d_t = a) - u_t(X_t, d_t = b) \\
&+ \delta \sum_{X_{t+1}} ln \left[P(d_{t+1} = j^{(t+1)} \mid X_{t+1})^{-1} \right] \times q(X_{t+1} \mid X_t, d_t = a) \\
&- \delta \sum_{X_{t+1}} ln \left[P(d_{t+1} = j^{(t+1)} \mid X_{t+1})^{-1} \right] \times q(X_{t+1} \mid X_t, d_t = b) \\
&+ \delta \sum_{X_{t+1}} \left[u_{t+1}(X_{t+1}, d_{t+1} = j^{(t+1)}) \right] \times q(X_{t+1} \mid X_t, d_t = a) \\
&- \delta \sum_{X_{t+1}} \left[u_{t+1}(X_{t+1}, d_{t+1} = j^{(t+1)}) \right] \times q(X_{t+1} \mid X_t, d_t = b) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} ln \left[P(d_{t+2} = j^{(t+2)} \mid X_{t+2})^{-1} \right] \\
&\times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = a) \\
&- \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} ln \left[P(d_{t+2} = j^{(t+2)} \mid X_{t+2})^{-1} \right] \\
&\times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = b) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} \left[u_{t+2}(X_{t+2}, d_{t+2} = j^{(t+2)}) \right] \\
&\times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = a) \\
&- \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} \left[u_{t+2}(X_{t+2}, d_{t+2} = j^{(t+2)}) \right] \\
&\times q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) \times q(X_{t+1} \mid X_t, d_t = b)
\end{aligned}
$$

Note that, the above value function difference appears in the standard choice probability of the Logit model. In a Logit model, it is the relative values (between choices) that matter, hence the above simplified result can be used to construct a log-likelihood function. Given the simplification, all of the structural parameters in the flow utility function $u(\cdot)$ become linear, which also makes the estimation of the model more computationally feasible. In addition, all of the conditional choice probabilities and transition probabilities can be replaced by some empirical estimates say $\widehat{Pr}(\cdot)$ and $\widehat{q}(\cdot)$, respectively. The log-likelihood is given by

$$L(\gamma,\delta) = \sum_i \sum_t ln\left(\frac{exp\,(v_{it}(X_{it},d_{it}=l))}{\sum_{j\in J} exp\,(v_{it}(X_{it},d_{it}=j))}\right) \tag{12}$$

or equivalently,

$$L(\gamma,\delta) = \sum_i \sum_t \left(v_{it}(X_{it},d_{it}=l) - ln \sum_{j\in J} exp\,(v_{it}(X_{it},d_{it}=j))\right) \tag{13}$$

where l is the observed crop choice made at field i in year t.

3. Data

This study assembles estimation data from four sources: (1) crop choice data from the 30*30 meter resolution Cropland Data Layer (CDL) developed by USDA National Agricultural Statistics Service; (2) groundwater level data from USGS National Water Information System database; (3) temperature and precipitation data from the PRISM project at Oregon State University; (4) crop price information from the New Mexico Annual Statistics Bulletins available up to 2018. We choose a study period of 2008 - 2018. 2008 is the first year that the CDL data is available for New Mexico. Figure 1 shows the study area (spans over four major crop production counties) and the recoded CDL raster for 2008.

The CDL data consists of a large panel of field-level crop choices, which is the dependent variable in this study. Most of New Mexico's crop production is located in the eastern High Plains (mainly in three counties: Curry, Quay, and Roosevelt). This study covers four major field crops in the region including hay, corn, sorghum, and winter wheat (the top crop). The original CDL data classifies land uses into more than 200 codes. This study recodes and keeps only the relevant land use: 1 = hay; 2 = corn; 3 = winter wheat; 4 = sorghum; 0 = idle land/pasture. All other small crops are excluded from the study given the small number of observations. The final data set only consists of pixels that have a value from $\{0,1,2,3,4\}$ in any year during the study period.

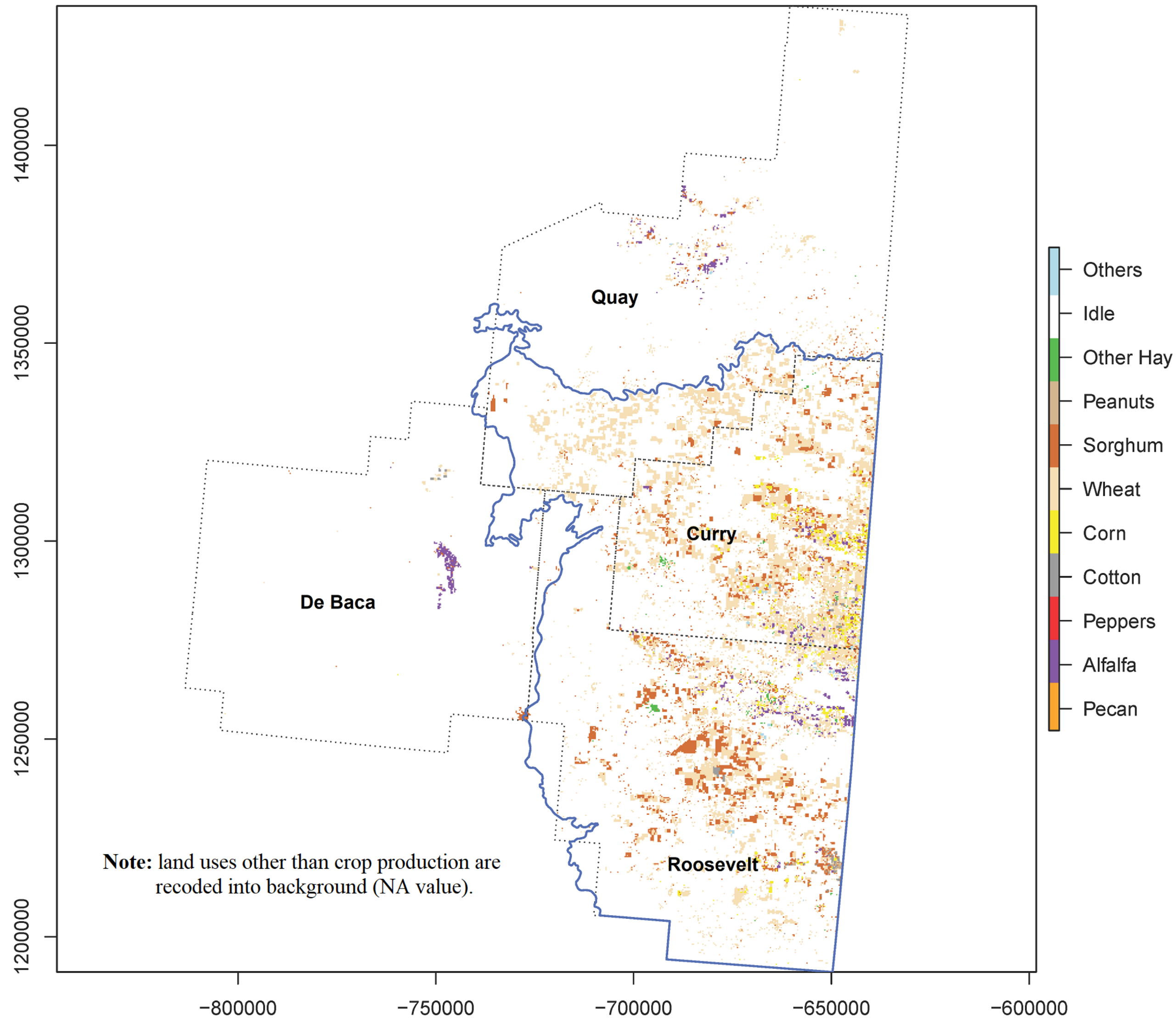

Fig. 1. The study area and CDL raster (recoded) for 2008

The groundwater depth measurements scatter across different wells in the study region. The USGS database tends to record different wells from year to year. To derive the depth of groundwater at each pixel, we spatially interpolate the depth using surrounding measurements for each year. The inverse distance weight is used for the interpolation, which is commonly adopted in hydrogeological studies. The range of spatial interpolation is chosen between 50km and 100km.

The growing season temperature and precipitation data are derived from the 4*4 km PRISM data. According to the New Mexico Annual Statistics Bulletins, the growing seasons for hay, corn, winter wheat, and sorghum are April to November, April to November, November to June, and May to December, respectively. These time frames are used to compute monthly average temperature and precipitation. All crop prices are recorded at the regional level. To match with CDL crop choice data, the climatic data are down-scaled to 30*30 meter resolution.

4. Estimation Procedure and Results

The empirical estimation carries out in two stages. The First stage is a spatial bootstrap process which randomly selects a panel of pixels from the raw data to reduce computational difficulty. Otherwise, a maximum likelihood estimation over billions of (30*30 meter) cells is computationally exhaustive. The second step is to repeat the first step enough times and compute empirical standard errors for all coefficient estimates. In the literature, spatial aggregation and random selection have been used to reduce the number of observations in estimation (e.g. Scott, 2014; Ji et al., 2014).

The preliminary results are presented in Tables 2 and 3. Here we ignore some of the control variables including crop prices and climatic variables, which all have expected impacts. For instance, an increase in the crop price will increase the likelihood of choosing that crop. The discussion of the results focuses on groundwater level and crop rotations, which are more policy-relevant. Note that for rotation variables, we focus on the two main crops: wheat and sorghum. This reduces the computational burden. Table 2 presents the estimation results with the groundwater depth (measured as water level, feet below land surface) spatially interpolated using well observations within a 100km radius. Note that the coefficient estimates here should be interpreted relatively. Over the study period from 2008 to 2018, the groundwater level has on average declined by 2.5 feet per year. The estimates across different crops suggest that, facing the decline of groundwater level (i.e. the increase of groundwater depth), high-value crops are more responsive. Looking at the two major crops (wheat and sorghum) in the study region, the likelihood of growing wheat is much higher than growing more drought-resistant sorghum. A potential explanation is that when the cost of irrigation by pumping groundwater increases, the farmers are more likely to choose high-value crops such as wheat.

Table 2: The impact of groundwater level on crop choices

	Crop Choice			
Variables	Hay	Corn	Wheat	Sorghum
g_{it}	0.0027 (0.0005)	0.0027(0.0003)	0.0031 (0.0001)	0.0017 (0.0002)
$W1$	-0.8774 (0.0825)	1.1130 (0.0393)	2.0651 (0.0156)	1.8945 (0.0278)
$S1$	-2.2417 (0.2265)	0.5452 (0.0591)	0.4016 (0.0248)	2.2769 (0.0314)
# of obs	117,480			

Note: (1) Standard errors are reported in parentheses and computed as the standard deviation of estimates from all random draws. (2) The estimates for $H1$ and $C1$ cannot be converged due to a lack of variation. Hay and corn take a small percentage of the total crop acreage in the study region.

Table 3 presents estimation results using the annual change of groundwater level. The idea is to incorporate the fact that groundwater depth has a lot of spatial heterogeneities due to the complicated hydrogeological conditions in the region (Rawling and Rinehart, 2017). Using the annual change of groundwater level as an explanatory variable can help to effectively difference out the spatial heterogeneity. The estimation results confirm the observation from previous results - farmers tend to respond to the decline of groundwater level by choosing high-value crops such as winter wheat instead of switching to more drought-resistant and water-saving crops such as sorghum.

Table 3: The impact of groundwater level change on crop choices

	Crop Choice			
Variables	Hay	Corn	Wheat	Sorghum
$\triangle g_{it}$	0.0022 (0.0004)	0.0022(0.0002)	0.0016 (0.0001)	0.0004 (0.0001)
$H1$	6.7740 (0.1242)	3.3629 (0.1526)	0.7401 (0.0976)	1.1686 (0.1564)
$C1$	2.3538 (0.2001)	4.7587 (0.0797)	1.2441 (0.0497)	1.5372 (0.0778)
$W1$	1.2996 (0.1218)	2.6323 (0.0666)	2.1453 (0.0160)	2.0093 (0.0292)
$S1$	-0.0761 (0.2435)	2.0525 (0.0799)	0.4760 (0.0250)	2.3874 (0.0327)
# of obs	117,480			

Note: standard errors are reported in parentheses and computed as the standard deviation of estimates from all random draws.

5. Conclusion

In this study, we develop a dynamic multinomial discrete choice model to estimate the impact of groundwater decline on crop choices in NM eastern High Plains. We take advantage of the recently available high-resolution remote sensing agricultural land cover data developed by the National Agricultural Statistics Service of USDA. The results show that farmers tend to respond to the decline of the groundwater level by choosing high-value crops such as winter wheat instead of switching to more drought-resistant crops such as sorghum. Both winter wheat and sorghum have been grown in the region historically. Therefore, switching cost is unlikely to explain the result. On the one hand, when the groundwater resource declines, farmers are forced to invest more to pump the same amount of water. Choosing a high-value crop justifies such a decision. On the other hand, this also reflects the common-pool resource problem of groundwater extraction. As the common-pool resource shrinks, users tend to increase the rate of extraction as a result of intensifying competition. This inflates the likelihood of choosing high-value crops instead of more drought-resistant options.

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