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Alternative models of input allocation in multicrop systems: Irrigation water in the Central Plains, United States

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Abstract

This paper compares three models of input allocation in multicrop systems. In addition to the variable input and satisficing models analyzed in previous research, an allocatable fixed input model of short-run input use is derived. The empirical application studies irrigation water use in the Central Plains region of the United States. Based on results from model specification tests and prediction accuracy measures, the allocatable fixed input model dominates both other models in explaining multicrop water allocation. In addition, the paper presents an alternative approach to the study of deficient data on multicrop production. By transferring econometric results from analysis of 'non-deficient' crop-level data, input allocations in deficient data sets can be predicted.

1. Introduction

A key problem in analysis of agricultural production involves predicting crop-level input allocation in a multioutput setting. Several researchers describe the problem as one of circumventing deficient data: given that data on crop-level input use commonly are not available (except for land use), the challenge is to develop modeling approaches that permit prediction of input allocations from data on farm-level input use and crop-level land use (Chambers and Just, 1989; Just et al., 1983; Just et al., 1990; and Shumway et al., 1984). One need for these modeling approaches arises from a professional responsibility to develop crop budgets and estimates of enterprise cost of production. For the U.S. Department of Agriculture in particular, cost of production studies are a U.S. congressional requirement that pose a special challenge because of deficient data (Just et al., 1990, hereafter JZHB). Further, environmental and health concerns associated with agricultural input use, such as nonpoint source pollution and food safety, have become important policy issues. Evaluating the effects of alternative policies for influencing input use frequently requires an understanding of how producers make decisions on crop-level input use.

One important distinction in the research on multicrop input allocation involves postulates

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about producer behavior in the short run. Two contributions to the literature adopt the conventional assumption of profit maximization (Chambers and Just, 1989; Just et al., 1983). An alternative postulate is satisficing behavior, i.e., that producers operate with rules-of-thumb emanating from bounded rationality (Simon, 1965; Nelson and Winter, 1982). A simple form of a satisficing model is that farmers follow either a distributor's recommendation or other routine practices concerning a crop's input application rate per acre. Crop acreage thus would effectively determine an input's allocation among crops on a multicrop farm. Recently, JZHB compared alternative models of short-run input use derived from these two behavioral postulates. Applying a data set on irrigated production in Israel, JZHB concluded that, based on model specification tests, a satisficing model explains short-run water allocation better than a variable input model derived with a primal, profit maximizing approach.

This paper expands the number of models considered relative to JZHB, comparing three alternative models of multicrop input allocation. We develop a fixed, allocatable input model in addition to the variable input and satisficing models studied previously. In the short run, an input typically considered to be a variable input in the long run may actually be fixed and allocatable. Irrigation with groundwater provides an illustration. Other researchers commonly model groundwater in the American West as a variable input in the long run (e.g., Caswell and Zilberman, 1985; Negri and Brooks, 1990; Nieswiadomy, 1988). This approach depicts groundwater as subject to market forces, with groundwater pumping cost serving as a water 'price'. Yet constraints on the number of wells, pump capacity, and water distribution infrastructure may make groundwater a fixed, allocatable input in the short run. Irrigation with surface water may pose similar short-run constraints, as well as long-run institutional constraints. Among other agricultural inputs, hired labor and farm machinery also may be variable in the long run, but fixed and allocatable in the short run.

To date, the fixed, allocatable input model has only been used to depict intermediate-run input use (Chambers and Just, 1989; Just et al., 1983; Moore and Negri, 1992). With land characterized as fixed and allocatable, the model served primarily as a mechanism for predicting short-run allocations of non-land inputs for the case of deficient data. This paper, in contrast, applies the allocatable fixed input model to directly explain short-run input use, thereby demonstrating the model's utility as a positive approach to explaining producer decisions.

Crop-level input use data are required to estimate the allocatable fixed input model. The model does not appear to be estimable or otherwise recoverable with deficient data, [1] which explains why the model is not considered in the recent literature on multicrop input allocation. We apply a data set that contains both crop-level irrigation water and acreage data from multicrop farms. The three alternative models of short-run input use thus can be directly estimated econometrically with the crop-level water data, rather than being predicted from implicit behavioral relationships using deficient data. The availability of crop-level microdata on water use effectively makes the data 'non-deficient' in terms of information on water allocation in a multicrop system.

Because of the use of crop-level input data, this paper contributes to the analysis of deficient data in a different way than previous studies. Rather than developing techniques to circumvent deficient data, we employ the non-deficient crop-level data to draw conclusions about which model of short-run water use is appropriate to apply to the case of deficient data. This creates the opportunity to apply parameters estimated with crop-level data to predict input allocations in deficient data sets. That is, econometric estimates of input

[1] Farm-level water use serves as an exogenous variable in the allocatable fixed input model, with crop-level water use serving as the endogenous variable (see Eq. 3). Unlike the variable input and satisficing models, a procedure does not appear to be available for predicting the results of the allocatable fixed input model using deficient data because of the essential role of farm-level water as an exogenous variable. In contrast, farm-level water serves as the endogenous variable in the variable input and satisficing models estimated with deficient data [see JZHB's (1990) equations (3) and (8)].

use equations that are obtained using crop-level data can be transferred to a deficient data set from a similar multicrop system. [2] Transferring econometric results in this way is both increasingly feasible as data become available from producer surveys that obtain crop-level input information and increasingly demanded for policy analysis of issues related to agricultural inputs. [3]

In this paper, two models - the variable input model and the fixed, allocatable input model - are derived from the profit maximization postulate using a dual approach. [4] The satisficing model, following JZHB, is a simple model of bounded rationality. These three models of multicrop water allocation are compared using two techniques of model selection: model specification tests and prediction accuracy measures. The empirical application studies multicrop groundwater irrigators in the Central Plains of the United States using data compiled by the U.S. Bureau of the Census from the 1984 and 1988 Farm and Ranch Irrigation Survey.

2. Three models of short-run input use

This section develops three models of short-run input use on a multicrop farm. While we develop the models in terms of irrigation water, the procedures are perfectly general and can be applied to any input.

The definition of the short-run production period used here applies the same definition used in previous research on irrigated agriculture (Chambers and Just, 1989; Just et al., 1983; JZHB, 1990). Nevertheless, the nature of short-run water use in a multicrop system needs to be characterized concretely. In this setting, the producer already has made an intermediate-run decision: choices have been made concerning the set of crops to grow and the acreage in each crop. The subsequent short-run decision involves deciding the quantity of irrigation water to apply to each crop over the irrigation season. Thus, as in the previous research, crop-specific acreages are exogenous to the water use decisions. The common thread across the three alternative models analyzed here is that crop-level land use serves as one determinant of crop-level water use in each model. The models differ in their answer to the following question: other than crop acreage, what other factors affect short-run, crop-level water use?

The following assumptions and notation apply throughout the paper. Producers take prices as given. Notation includes: $\boldsymbol{p}$ is a vector of crop prices; p_i is price of crop i ($i = 1, \ldots, m$); r_w is water price; $\boldsymbol{r}$ is a vector of variable input prices other than water ($v = 1, \ldots, z$); w_i is water allocated to crop i; W is farm-level quantity of water; n_i is land allocated to crop i; $\boldsymbol{x}$ is a vector of variables taken as given in the short run (e.g., crop-level irrigation technology and weather; $s = 1, \ldots, t$); $\pi_i(\cdot)$ is the short-run restricted profit function of crop i; and $\Pi(\cdot)$ is the multioutput restricted profit function of the firm. Input nonjointness is assumed, so that the multioutput profit function decomposes into the sum of distinct crop-specific profit functions. The profit functions are assumed to be well-behaved in terms of the conventional assumptions.

The study applies the normalized quadratic profit function as the form of the crop-specific restricted profit functions. The normalized quadratic is a flexible functional form of the profit function (Lau, 1978), and has been used previously in multioutput agricultural production research (e.g., Huffman, 1988; Shumway, 1983). Its full specification includes linear, squared, and cross-product terms for all exogenous variables. Prices are expressed in relative terms, with one

[2] The idea proposed here of transferring econometric results from a 'non-deficient' data set to a deficient data set is analogous to the topic of transferring benefit estimates in the case of measuring unmarketed benefits of environmental assets. This topic was the focus of a 1992 workshop, 'Benefits Transfer: Procedures, Problems, and Research Needs', sponsored by the Association of Environmental and Resource Economists (Kealy et al., 1992).

[3] At the same time, econometric results should be transferred only when strong economic and physical parallels exist between the original research setting and the transfer setting.

[4] This paper does not address the merits of primal versus dual approaches, which has been an important topic in this literature (Chambers and Just, 1989; Just et al., 1983; Zilberman, 1989).

price serving as a numeraire; this maintains linear homogeneity of the function. [5] As will become evident, the main advantage of the normalized quadratic form enters when developing the fixed, allocatable input model.

2.1. Variable input model

A variable input model has commonly been applied to analysis of short-run irrigation water use (Chambers and Just, 1989; Just et al., 1983; JZHB, 1990). When following the dual approach, application of Hotelling's lemma in terms of the water price variable generates crop-level water demand functions for this model. These are:

$$-\frac{\partial \pi_i(p_i,\boldsymbol{r},r_W,n_i;\boldsymbol{x})}{\partial r_W} = w_i(p_i,\boldsymbol{r},r_W,n_i;\boldsymbol{x})$$

$$i = 1,\ldots,m \qquad (1)$$

The estimable form for each crop-level water demand function, given the use of normalized quadratic restricted profit functions, is a linear function of the independent variables.

2.2. Fixed, allocatable input model

The fixed, allocatable input model of water use provides a second approach based on a profit maximization postulate. The short-run water constraint applied in this model is a groundwater constraint; it essentially represents the fixity of groundwater wells, pump capacity, and irrigation capital during the growing season. The constraint does not reflect a long-run, institutionally-defined water quota, as groundwater is commonly modelled as subject to market forces. The approach uses duality, thereby following conceptual methods developed for analysis of fixed, allocatable inputs (Chambers and Just, 1989; Shumway et al., 1984). To obtain optimal short-run water allocation functions, we solve the following constrained optimization problem:

$$\Pi(\boldsymbol{p},\boldsymbol{r},n_1,n_2,\ldots,n_m,W;\boldsymbol{x}) \qquad (2)$$

$$= \underset{w_1,\ldots,w_m}{\text{MAX}} \left[\sum_{i=1}^{m} \pi_i(p_i,\boldsymbol{r},n_i,w_i;\boldsymbol{x}) : \sum_{i=1}^{m} w_i = W \right]$$

An equation system for solving (2) for an interior solution contains two general elements, the set of necessary conditions for an interior solution and the water constraint. The necessary conditions are $\partial\pi_i(p_i, \boldsymbol{r}, n_i, w_i; \boldsymbol{x})/\partial w_i = \lambda$ for $i = 1, \ldots, m$, where λ is the shadow price on the water constraint. Optimal water allocation functions follow from solving this equation system; these functions are:

$$w_i^* = w_i^*(\boldsymbol{p},\boldsymbol{r},n_1,n_2,\ldots,n_m,W;\boldsymbol{x}) \quad i = 1,\ldots,m \qquad (3)$$

Note two distinct features of the allocatable fixed input model. First, water allocations to one crop depend on the output prices and acreage levels of all other crops. Thus, in contrast to the variable input model of Eq. (1), intercrop price and acreage variables supplement own-crop price and own-crop acreage as determinants of water use. Second, the farm-level water quantity constraint in (3) replaces water price as a determinant of short-run crop-level water use.

Use of normalized quadratic profit functions enables a closed-form solution to (2). The equation system that must be solved, composed of the necessary conditions and the constraint, is a linear system. Thus, the $w_i^*(\boldsymbol{p},\boldsymbol{r},n_1,n_2,\ldots,n_m,W;\boldsymbol{x})$ that explicitly solve (2) are linear in the exogenous variables; this function is the estimable form for this model. The optimization problem developed here follows procedures used for a similar problem (Moore and Negri, 1992, pp. 31–33).

The optimal water allocation equations in (3) illustrate the apparent jointness created by fixed, allocatable inputs (Chambers and Just, 1989; Shumway et al., 1984). Despite the assumption of input nonjointness, the fixed water input creates interdependence across crops. For instance, consider a multicrop farm that grows alfalfa, corn, and dry beans. With apparent jointness, water use on corn depends on acreage in alfalfa and

[5] To simplify notation, interpret output and input prices in Eqs. (5), (7) and (9) as relative prices because they are derived from normalized quadratic profit functions.

acreage in dry beans *in addition to* acreage in corn.

2.3. Satisficing model

The satisficing model of short-run water use follows closely the 'behavioral approach' of JZHB: crop-level land use virtually determines crop-level water use, with all price variables and the water constraint removed from the specification. Other variables (irrigation technology and weather) explain any additional variation in water use. The general form of this model is:

$$w_i = w_i(n_i; \boldsymbol{x}) \quad i = 1, \ldots, m$$

We adopt a linear specification to estimate (4). This is consistent with JZHB (1990) and the earlier two models of this paper.

In intuitive terms, the satisficing model is premised on the idea that longer-run decisions have a larger quantitative impact on profit relative to short-run decisions. Thus, producer behavior might conform more closely to the profit maximization postulate in the intermediate- or long-run periods. However, satisficing in the short run by following a rule-of-thumb or a distributor's recommendation may conserve on information requirements with little sacrifice in profit.

3. Model specification tests and prediction accuracy measures

This section describes the model specification tests and prediction accuracy measures that are applied in the research. The three models of short-run water use are compared using model specification tests. Two models are compared at a time. The multicrop approach developed here applies the hypothesis tests as farm-level tests. That is, the approach characterizes producer behavior on the entire multicrop operation, rather than crop-by-crop behavior, by analyzing which model best represents aggregate, farm-level behavior. Each comparison of farm-level models thus is executed as a single-equation test for the set of m crops. To implement this, the crop-level water use data are combined simply by stacking the system of observations.

First, consider the model specification test for the variable input model and the satisficing model. This comparison involves a nested F-test. The empirical specification of the variable input model of Eq. (1), given use of normalized quadratic profit functions, is:

$$w_i = \alpha^i + \beta^i p_i + \sum_{v=1}^{z} \gamma_v^i r_v + \delta^i r_W + \theta^i n_i + \sum_{s=1}^{t} \eta_s^i x_s \qquad i = 1, \ldots, m \tag{5}$$

where the coefficients are parameters to be estimated. The satisficing model of water use (Eq. 4) is represented by a subset of variables in Eq. (5), including crop acreage (n_i) and short-run elements of weather, irrigation technology, and water management ($\boldsymbol{x}_s$). Thus, in terms of a classical F-test, the null hypothesis is that:

$$\beta^i = \gamma_v^i = \delta^i = 0 \quad \begin{matrix} i = 1, \ldots, m \\ v = 1, \ldots, z \end{matrix} \tag{6}$$

That is, the null hypothesis is true [6] - and the satisficing model is the preferred model - if the coëfficients on own-crop price, variable input prices, and water price are equal to zero. Otherwise, if the alternative hypothesis is true, the variable input model is the preferred model specification.

Second, consider the model specification test for the fixed, allocatable input model and the satisficing model. This comparison also involves a nested F-test. The empirical specification of the allocatable fixed input model of Eq. (3) is:

$$w_i = \alpha^i + \sum_{j=1}^{m} \beta_j^i p_j + \sum_{v=1}^{z} \gamma_v^i r_v + \sum_{k=1}^{m} \theta_k^i n_k + \psi^i W + \sum_{s=1}^{t} \eta_s^i x_s \quad i = 1, \ldots, m \tag{7}$$

Here, the null hypothesis is that the coefficients on crop prices, variable input prices, crop acreages (other own-crop acreage), and the farm-level water constraint are equal to zero, or

$$\beta_j^i = \gamma_v^i = \theta_k^i = \psi^i = 0 \quad \begin{matrix} i = 1, \ldots, m \\ j = 1, \ldots, m \\ v = 1, \ldots, z \\ k = 1, \ldots, m \quad i \neq k \end{matrix} \tag{8}$$

[6] We use 'true' as a simple way of expressing the more technical phrase 'fail to reject'.

The satisficing model is the preferred model specification if the null hypothesis is true. Otherwise, if the alternative hypothesis is true, the allocatable fixed input model is the preferred specification.

Third, consider the model specification test for the variable input and fixed input models. This comparison involves a non-nested hypothesis test using a non-nested F-test (Fomby et al., 1984, pp. 415-416; Pesaran, 1974). [7] The non-nested F-test's artificial nesting model includes every exogenous variable for the five crops' water use equations from these two models (i.e., combining Eqs. 5 and 7). In general terms this is $w_i(\boldsymbol{p},\boldsymbol{r},r_w, n_1,n_2,\ldots,n_m,W;\boldsymbol{x}), i = 1,\ldots,m$. The empirical specification of the artificial nesting model is:

$$w_i = \alpha^i + \sum_{j=1}^{m} \beta_j^i p_j + \sum_{v=1}^{z} \gamma_v^i r_v + \delta^i r_W + \sum_{j=1}^{m} \theta_j^i n_j + \psi^i W + \sum_{s=1}^{t} \eta_s^i x_s \quad i=1,\ldots,m \tag{9}$$

The performance of the variable and fixed input models are compared, independently, to the performance of the artificial nesting model. Water prices are the elements of the artificial model that are unique to the variable input model. Thus, the first stage of the non-nested F-test is to test the null hypothesis that the coefficients on water price are equal to zero, or:

$$\delta^i = 0 \quad i = 1,\ldots,m \tag{10}$$

If the null hypothesis is true, then the variable input model is rejected relative to the artificial nesting model. Otherwise, if the alternative hypothesis is true, then the variable input model is accepted as the preferred specification relative to the artificial nesting model. The second stage of the non-nested F-test is to reject the fixed, allocatable input model if elements unique to that model (the farm-level water constraint and intercrop interdependencies in crop prices and acreages) do not independently explain variation in water use. The null hypothesis for this test is:

$$\beta_j^i = \theta_j^i = \psi^i = 0 \quad \begin{matrix} i = 1,\ldots,m \\ j = 1,\ldots,m \end{matrix} \quad i \neq j \tag{11}$$

Otherwise, if the alternative hypothesis is true, then the allocatable fixed input model is accepted as the preferred model specification relative to the artificial nesting model. As with all non-nested tests, both models can be rejected, both can be accepted, or only one model can be rejected.

The set of three model specification tests can yield either determinate or indeterminate results on model choice. For example, an indeterminate result would occur if: the satisficing model is chosen over the variable input model in the first test; the allocatable fixed input model is chosen over the satisficing model in the second test; but then the variable input model is chosen over the allocatable fixed input model in the third test. In contrast, a model will dominate if it is chosen in each of the two tests in which it participates directly.

The prediction accuracy measures supplement findings from the model specification tests. Three different measures are applied to compare the models, including mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). [8] As with the model specification tests, the prediction measures are developed using a farm-level approach. The

[7] We use a non-nested F-test rather than a J-test because of the use of limited-dependent variable econometric methods in the empirical application. The J-test requires that error terms are iid normal (Davidson and MacKinnon, 1981, pp. 781-782). Error terms of limited-dependent variable models are not so distributed.

[8] These three measures are commonly applied measures of prediction accuracy (Kost, 1980). Their general formulas are:

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T} |\hat{Y}_t - Y_t|$$

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (\hat{Y}_t - Y_t)^2}$$

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T} \left[\frac{|\hat{Y}_t - Y_t|}{Y_t}\right]$$

where Y_t is the observed dependent variable for observation t, $\hat{Y}_t$ the predicted dependent variable for observation t, and T the number of observations.

measures thus represent the accuracy of a model in predicting short-run water use for the set of m crops under consideration. The approach is not conducted crop-by-crop.

Four sets of predictions are made, including one in-sample prediction and three out-of-sample predictions. [9] Applying the three measures to each of the four predictions generates twelve cases for evaluating the alternative models.

The ability to apply prediction accuracy measures demonstrates another advantage of crop-level input data relative to deficient data. With deficient data, predictions of crop-level input use from one model can be compared to predictions from another model. However, the predictions cannot be compared to actual input use, which is the preferred benchmark for comparison.

4. Data, variables, and econometric model

The econometric analysis considers multicrop producers engaged in irrigated agriculture in the U.S. Central Plains region (the states of Colorado, Kansas, Nebraska, and Wyoming). Producers are multicrop growers who choose among five field crops commonly grown as part of a multicrop system in the region: alfalfa hay, barley, corn for grain, dry beans, and wheat. The producers in the sample irrigate with groundwater only or with groundwater and surface water. Groundwater is assumed to be the marginal water source when both sources are used (as in Negri and Brooks, 1990). Groundwater pumping lift is translated into a marginal groundwater pumping cost through an engineering formula (see Appendix); this cost serves as the measure of water price.

The primary data for the analysis are from the 1984 and 1988 Farm and Ranch Irrigation Survey (FRIS) (USDC, 1986; USDC, 1990). The dependent variables for the analysis are created from survey questions on irrigation water use by crop. The survey also includes questions on crop-level acreage and irrigation technology, as well as questions on on-farm irrigation practices (e.g., water sources, groundwater depth, and water management practices); several independent variables are formed from these data. The Appendix defines the sample, data, and variables more extensively, and also includes a table of descriptive statistics for key variables.

Secondary data sources are used to create variables that are merged with the FRIS-based variables. Three categories of variables are developed: output and input prices; climate and weather; and soil. Crop price variables are constructed as expected 1984 and 1988 prices. Variable input prices are current-year prices based on 1984 and 1988 data. Climate variables represent expected weather conditions. They help to explain discrete choices concerning which crops to grow. Weather variables represent actual 1984 and 1988 weather conditions. They help to explain short-run decisions on water-use quantity. Soil variables represent quality dimensions of cropland. The Appendix also defines these data and variables more extensively.

The availability of microdata on multicrop production presents an econometric issue concerning application of an unbiased estimator. [10] Producers grow two or more of the five crops in the multicrop system. Of a sample of 766 farms, non-limit observations by crop (i.e., farms growing that crop) are: alfalfa, 464; barley, 96; corn, 667; dry beans, 191; and wheat, 446. Thus, a limited-dependent variable econometric model must be applied to produce unbiased estimates (Huffman, 1988). This paper applies the Heck-

[9] For an out-of-sample prediction, the observations are randomly divided into two subsets, one with 80% of the observations and one with the remaining 20% of the observations. The 80% subset is used to estimate each model's parameters. These parameter estimates are applied to the 20% subset to make out-of-sample predictions and to apply the prediction accuracy measures. This procedure is repeated three times.

[10] A second issue related to multicrop systems concerns efficient estimates. As stated by Shumway et al. (1984, p. 75), with multioutput systems, "...efficient econometric estimation generally requires estimation of a seemingly unrelated multiple-product system." This paper applies a limited-dependent variable model to obtain unbiased estimates instead of addressing efficiency.

Table 1
Performance of three models in predicting short-run water use

Type of prediction	Prediction accuracy measure		
Model of water use	Mean absolute error (MAE)	Root mean square error (RMSE)	Mean absolute percentage error (MAPE)
In-sample predictions			
Variable input model	256.2	538.5	137.5
Fixed, allocatable input model	190.5 [b]	348.3 [b]	131.2 [b]
Satisficing model	256.5	545.9	137.2
Out-of-sample predictions [a]			
Draw 1			
Variable input model	270.4	527.8	186.6 [b]
Fixed, allocatable input model	222.2 [b]	410.1 [b]	221.6
Satisficing model	283.3	541.5	193.1
Draw 2			
Variable input model	280.9	864.6	211.5
Fixed, allocatable input model	223.5 [b]	499.9 [b]	237.2
Satisficing model	284.3	874.1	181.0 [b]
Draw 3			
Variable input model	293.6	533.6	224.6
Fixed, allocatable input model	208.1 [b]	340.4 [b]	190.7 [b]
Satisficing model	289.1	539.1	197.2

[a] For an out-of-sample prediction, the observations are randomly divided into two subsets, one with 80% of the observations and one with the remaining 20% of the observations. The 80% subset is used to estimate each model's parameters. These parameter estimates are applied to the 20% subset to make out-of-sample predictions and to apply the prediction accuracy measures. This procedure is repeated three times.
[b] Indicates the model that most accurately predicts short-term water use for a given accuracy measure and experiment.

man model (Maddala, 1983). Limited-dependent variable models, such as the Heckman and Tobit models, decompose a decision into a discrete-choice decision (on whether to grow a particular crop) and a quantity decision (on the level of input use). The Heckman, unlike the Tobit, permits the set of exogenous variables explaining the crop-choice decision to vary from the set of exogenous variables explaining the water quantity decision. [11]

The decision framework for the Heckman model is appropriate for analysis of short-run irrigation water use. The discrete decision to use water is influenced by the same variables affecting the intermediate-run decision associated with irrigated land allocation: a decision to allocate land to a crop means that irrigation water will also be applied to that crop. These intermediate-run variables include farm-level exogenous variables (e.g., farm-level irrigation technology and climate variables). The quantity of water used during the irrigation season, however, depends on short-run exogenous variables. These include crop acreage levels (which are set endogenously in the intermediate run), crop-level irrigation technology, and weather variables.

5. Empirical results

5.1. Comparison of alternative models

The main empirical result is the comparison of alternative models using the model specification

[11] Bockstael et al. (1990) discuss the appropriate use of alternative limited-dependent variable econometric models (Heckman, Tobit and Cragg) in the analysis of recreation demand. Their discussion had useful application to this paper.

tests and prediction accuracy measures. In the model specification tests, the fixed, allocatable input model of short-run water use dominates the other two models as a way of explaining producer decisions. Specifically, one model specification test involves the nested test comparing the fixed input and satisficing models (Eq. 8). The F-test value is 18.30 in this test, thus implying that the coefficients in the fixed input model are statistically different from zero at the 0.01 level (in a test with 55 restrictions). The fixed input model has substantial explanatory power beyond the satisficing model.

A second specification test is the non-nested test comparing the variable input model and the fixed input model. In one component of the test, which compares the artificial nesting model and the fixed input model (Eq. 11), the F-test value is 21.61. Thus, the fixed input model is not rejected at the 0.01 level in this component of the non-nested test (in a test with 45 restrictions). The F-test value is 0.90 in evaluation of the variable input model in the second component of the test (Eq. 10). The variable input model is rejected at the 0.01 level (in an F-test with five restrictions). The non-nested hypothesis test, therefore, reaches an unambiguous conclusion: the allocatable fixed input model is chosen over the variable input model.

At this point, the model specification tests already yield a conclusion in favor of the allocatable fixed input model. The final test, which compares the variable input and satisficing models (Eq. 6), is irrelevant because of the fixed input model's dominance. It is interesting to note, nevertheless, that the test chooses the satisficing model over the variable input model.

Application of the three prediction accuracy

Table 2
Estimates of short-run water use, allocatable fixed input model [a]

Independent variable	Alfalfa	Barley	Corn	Dry beans	Wheat
ALFPRC	58.466 *	11.462	−5.323	1.578	12.842
BARPRC	−690.89 *	−83.082	69.864	−52.962	−168.65
CRNPRC	6804.2 *	745.33	67.346	107.29	312.58
DBNPRC	318.38 **	65.294	−49.879	8.353	28.125
WHTPRC	−8588.2 *	−1579.6	1002.8	−100.02	−677.31
WAGE	−195.72	155.60	−175.69	−101.06	9.169
ALFACR	1.475 **	−0.278 **	−1.028 **	−0.316 **	−0.299 **
BARACR	−0.213	1.308 **	−1.423 **	−0.545 **	−0.265
CRNACR	−0.466 **	−0.078	0.886 **	−0.196 **	−0.277 **
DBNACR	0.021	−0.190	−0.600 **	0.799 **	−0.056
WHTACR	−0.430 **	−0.282 **	−0.727 **	−0.056	1.037 **
TOTWTR	0.239 **	0.088 **	0.485 **	0.139 **	0.137 **
DMSRWT	−6.964	66.332	−126.49 **	13.954	−94.611
DMOWNTC	−28.729	−44.167	−60.504	15.163	18.731
DMNOWT	26.245	10.043	−12.072	−27.321	90.272
DMHGMG	−44.628	4.290	−29.580	−4.222	−49.736
DMLWMG	40.268	−6.311	1.915	−22.593	52.050
OWNCDD	0.095 *	0.007	0.003	−0.001	0.009
OWNPCP	9.858	−0.824	−3.725	4.995	−8.641
SAND	−54.711	−296.86	49.225	78.484	−228.95 **
INTERCEPT	2181.0 *	730.42	−1457.7	326.28	126.85
Adjusted R^2	0.903	0.749	0.959	0.900	0.839

* and ** denote significance at the 0.05 and 0.01 levels, respectively.
[a] Dependent variable is crop-level water use. The Appendix contains definitions of the independent variables.

Table 3
Estimates of short-run water use, variable input model [a]

Independent variable	Alfalfa	Barley	Corn	Dry beans	Wheat
OWNPRC	2.570	26.453	846.87 **	3.848	115.96
WTRPRC	−3.776	−0.735	3.562	3.825	2.991
WAGE	−176.57 *	104.46	−422.52 **	−109.33 *	−11.951
OWNACR	2.059 **	1.284 **	1.956 **	0.982 **	1.216 **
DMSRWT	26.369	103.29 *	−148.01	18.066	9.992
DMOWNTC	−70.676	−84.958	−237.95 **	−8.064	−42.420
DMNOWT	−13.086	32.987	52.378	−19.619	90.671 *
DMHGMG	−36.694	5.308	62.336	15.355	−21.351
DMLWMG	114.14	−2.706	147.44	−16.886	99.343
OWNCDD	0.097	−0.028	0.233 **	0.119 *	0.031
OWNPCP	6.099	8.634	−26.789 *	−5.732	−4.558
SAND	79.340	−122.17	175.73	167.15 **	−31.228
INTERCEPT	194.90	−410.55	−1049.7 *	172.20	−546.63 **
Adjusted R^2	0.825	0.637	0.876	0.782	0.777

* and ** denote significance at the 0.05 and 0.01 levels, respectively.
[a] Dependent variable is crop-level water use. The Appendix contains definitions of the independent variables.

measures provides additional evidence on model choice. [12] With the in-sample prediction, the fixed, allocatable input model outperforms the two alternative models according to each of the three measures (MAE, RMSE, and MAPE) (see Table 1). Results with the three out-of-sample predictions show slightly less consistency. For both the MAE and RMSE measures, the allocatable fixed input model outperforms the other two models in each of the three predictions. With the MAPE measure, however, each of the three models outperforms the other two in one prediction. Nevertheless, the weight of the evidence supports the conclusion that was drawn from the model specification tests. The fixed, allocatable input model provides a better model for explaining short-run water allocation in multicrop systems than either the variable input or satisficing model.

Additional understanding is useful of the factors motivating the choice of the allocatable fixed input model. A key factor is the multicrop jointness evident in the crop acreage variables. For each of the five crops, water use depends strongly on acreage in some or all of the other four crops ($\partial w_i/\partial n_j$, $i \neq j$) (Table 2). For example, the quantity of water applied to corn depends negatively on alfalfa acreage, barley acreage, dry beans acreage, and wheat acreage, with each of these variables significant at the 0.01 level. Overall, 13 of the 20 intercrop acreage variables are significant at the 0.01 level.

The relative performance of the water constraint variable and the water price variable also illuminates model specification. The water constraint is positive and significant at the 0.01 level in each equation of the allocatable fixed input model, with each t-statistic value exceeding 5.0. This certainly provides evidence that the producer perceives irrigation water as a fixed input in the short run. In contrast, water price is not negative and significant for any of the crops when estimated with the variable input model (Table 3). After planting crops, irrigators do not respond to water price in subsequent short-run decisions. This occurs despite clear statistical evidence that the water price variable influences longer-run decisions on cropland allocation in multicrop sys-

[12] The predictions are made using only non-limit observations, with the limit observations excluded from this portion of the analysis. This use of the data is appropriate given, in practical terms, what we are trying to predict. The goal is to predict crop-level water use given knowledge of crop-level land allocations on a multicrop farm. Consider a case of a producer who allocates no acreage to a certain crop. In this case, the analyst knows that water use on that crop is zero. This does not need to be confirmed with a prediction; it is a deterministic relationship. Thus, only non-limit observations of water use are applied to evaluate the prediction accuracy of the models.

Table 4
Estimates of short-run water use, satisficing model [a]

Independent variable	Alfalfa	Barley	Corn	Dry beans	Wheat
OWNACR	2.070 **	1.270 **	1.958 **	0.961 **	1.206 **
DMSRWT	2.789	114.73 *	−148.10	27.838	16.618
DMOWNTC	−110.63 *	−74.96	−202.19 **	16.679	−27.488
DMNOWT	−14.735	55.605	43.756	−20.309	90.527
DMHGMG	−36.607	0.401	50.630	22.253	−13.303
DMLWMG	117.86	−5.659	137.52	−15.525	99.909
OWNCDD	0.083	−0.010	0.178 **	0.110 *	0.033
OWNPCP	−7.147	7.570	−33.510 **	−8.147	4.224
SAND	21.515	−135.21	106.01	125.22 *	−27.978
INTERCEPT	−179.72	7.44	−463.20 **	−109.39	−201.84
Adjusted R^2	0.824	0.636	0.873	0.775	0.775

* and ** denote significance at the 0.05 and 0.01 levels, respectively.
[a] Dependent variable is crop-level water use. The Appendix contains definitions of the independent variables.

tems in the Central Plains. [13] That is, groundwater is a variable input in the intermediate to long run, yet an allocatable fixed input in the short run.

The performance of the price variables in the variable input model explains the choice of the satisficing model (Table 4) over the variable input model in the model specification test. The water price variables, as noted before, are statistically insignificant. Only corn price is significant of the five own-crop output prices. The wage rate variable, though significant in three of five equations, apparently does not explain much variation; adjusted R^2s are only slightly higher in the variable input model than the satisficing model.

5.2. Results with the fixed, allocatable input model

As the model that performs best in explaining short-run water use, the allocatable fixed input model needs additional description; four points follow. First, the adjusted R^2 values indicate that the model performs well in explaining crop-level water use in this multicrop system (Table 2). The adjusted R^2s meet or exceed 0.90 for alfalfa, corn, and dry beans. Even the lowest value, 0.749 for barley, indicates relatively strong performance for a data set reliant on cross-sectional variation.

Second, consider the influence of own-crop acreage variables. Each of these acreage variables, not surprisingly, is significant in explaining water use; each t-statistic value on this set of variables exceeds 10.0. The coefficients on own-crop acreage show how a marginal increase in the crop's acreage increases water allocated to the crop for producers growing the particular crop.

Third, in terms of intercrop interdependence, a change in acreage of one crop induces water reallocation among other crops given that water is a fixed, allocatable input. Take the alfalfa-corn relationship as an example. The coefficient on alfalfa acreage in the corn water allocation equation is −1.028. A one-acre increase in alfalfa acreage thus would reduce corn water use by slightly more than an acre-foot. Reciprocally, the coefficient on corn acreage in the alfalfa water allocation equation is −0.466, with a similar interpretation holding.

More generally, the performance of the intercrop acreage variables demonstrates the competition among crops in a multicrop system for a fixed quantity of water. Note that, when a particular intercrop acreage variable is significant, its

[13] Three sets of equations representing longer-run decisions - crop supply, land allocation, and crop-choice equations - were estimated using the identical data set as applied here (Moore et al., 1994). The water price variable typically is statistically significant in each set of equations. By crop, the t-statistic values on water price in the crop supply equations are: alfalfa, −3.37; barley, −3.18; corn, 2.36; dry beans, 1.07; and wheat, 2.01. For the land allocation equations, the t-statistic values are: alfalfa, −3.99; barley, −3.14; corn, 2.42, dry beans, 1.11; and wheat, 2.02. For the crop-choice decision, the t-statistic values for the water price variable are: alfalfa, −3.54; barley, −2.32; corn, 1.78, dry beans, 1.38; and wheat, 2.86.

coefficient is negative. Thus, an increase in an intercrop acreage variable reduces the quantity of water applied to a competing crop. This relationship illustrates the nature of a fixed, allocatable input in a short-run, multicrop system. The farm-level input constraint creates the competition among crops for the input. Thereafter, the crop-level acreage quantities become important determinants of the division of the fixed input.

Fourth, estimates on the water constraint variable indicate the allocation among crops of a marginal increase in farm-level water availability for producers growing the particular crop. The individual coefficients on the water constraint are: corn, 0.485; alfalfa, 0.239; dry beans, 0.139; wheat, 0.137, and barley, 0.088. These indicate that increases in water availability are allocated most heavily to crops with relatively high water requirements (corn and alfalfa) rather than to crops with relatively low water requirements (dry beans, wheat, and barley).

6. Summary and conclusions

This paper compares three alternative models of short-run input use in multicrop systems: a variable input model, an allocatable fixed input model, and a satisficing model. The fixed, allocatable input model has not been analyzed in previous research on this topic. The empirical application studies irrigation water use on multicrop farms in the Central Plains of the United States. The main finding is that the fixed, allocatable input model explains multicrop water use better than the other two models. It was chosen over the other two models in model specification tests and outperformed the others in ten of twelve cases of prediction accuracy measurement.

In this initial application to the short run, the allocatable fixed input model provides new insight into the determinants of producer decisions. The farm-level water constraint performs well statistically and intuitively as a variable explaining multicrop water allocation. Further, the intercrop acreage variables demonstrate clearly the competition among crops for the fixed farm-level water quantity. One result provides an example: water applied to corn depends negatively on alfalfa acreage, barley acreage, dry beans acreage, and wheat acreage, with each of these variables significant at the 0.01 level. This is the essence of apparent jointness in the short run.

Crop-level input use data are necessary for application of the fixed, allocatable input model. The model cannot be applied directly to deficient data sets, which are commonly defined as containing crop-level acreage data and farm-level input data. Instead, the model can be applied indirectly to deficient data by transferring parameter estimates from a model application that uses non-deficient, crop-level data. For instance, it may be feasible to transfer parameter estimates from these results to a data set compiled by the Bureau of Reclamation (BOR) on agriculture in BOR-served irrigation districts in the Central Plains region. The BOR data are a deficient data set, containing information on crop-level irrigated acreage and district-level water use, but not on crop-level water use (Moore and Negri, 1992). In transferring the econometric results, crop-level water use could be predicted for irrigation districts served by BOR water projects in the Central Plains.

While the paper studies irrigation with groundwater, other agricultural inputs - such as surface water, hired labor, family labor, and farm machinery - may be fixed and allocatable in the short run. Since the allocatable fixed input model cannot be applied without crop-level data, acquiring and analyzing data on these inputs must precede a second-stage effort to transfer results to deficient data sets. This paper's findings indicate that acquisition of improved, crop-level data may be necessary for a better understanding of producer decisions in multicrop systems.

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Appendix

Data description and variable definitions

The primary data in this study are from the 1984 Farm and Ranch Irrigation Survey and the 1988 Farm and Ranch Irrigation Survey (FRIS), a mail survey of operators of irrigated farms (USDC, 1986; USDC, 1990). The 1984 (1988) FRIS samples respondents to the 1982 (1987) Census of Agriculture who reported irrigated land. Both surveys are stratified random samples of irrigated farms, representing 6% and 7% of the 1982 and 1987 Census of Agriculture, respectively. These primary data are combined with price, climate and weather, and soil quality data from secondary sources to complete the data set.

The study considers farms in the U.S. Central Plains region of Colorado, Kansas, Nebraska, and Wyoming. Irrigated farms and acres in Nebraska and Kansas dominate this region in both FRIS population estimates and the data for this study. In 1988, irrigation wells are reported as the primary water source in these two states, with 83% of the farms reporting at least one pumped well. Farms with wells irrigate 89% of total irrigated acres and apply 87% of total irrigation water in the region.

FRIS variables. The FRIS includes crop-level data on irrigation water and land use. It also includes crop-level qualitative information on irrigation technology use, farm-level irrigation technology use in acres, and farm-level qualitative information on water management. Table 5 reports descriptive statistics for selected FRIS variables.

The 766 farms included in this study grow at

Table 5
Descriptive statistics for selected variables, Central Plains region

Item Units	Measure	Total farm	Crop [a]				
			Alfalfa	Barley	Corn	Dry beans	Wheat
Number of farms		766	464	96	667	191	446
Land	Mean	1455	281	205	772	294	424
(acres)	SD [b]	1587	539	256	1001	337	530
Water applied	Mean	2074	503	269	1224	324	429
(acre-feet)	SD [b]	2967	1232	403	2067	377	1246
Water application rate (acre-feet/acre)	Average	1.4	1.8	1.3	1.6	1.1	1.0
Remaining variables are not applicable to particular crops							
Water price	Mean	16.81					
($/acre-foot)	SD [b]	7.18					
Pumping depth	Mean	99					
(feet)	SD [b]	69					
Pumping pressure	Mean	39					
(psi)	SD [b]	20					
Farm characteristics (% of farms reporting the characteristic)							
Surface water available	%	23					
Pressure irrigation technologies	%	77					
Advanced water management methods used	%	37					
Fixed-time water management methods used	%	17					

[a] Crop-level descriptive statistics apply to farms growing that particular crop. Farms not growing the crop, which have a zero value for acreage and water use, are excluded from the calculations.
[b] SD is the standard deviation.

least two of five common irrigated field crops, including alfalfa hay, barley, corn for grain, dry beans, and wheat. They do not grow specialty crops (orchards, berries, and vegetables). The mean farm size is 1455 acres of harvested cropland. Farms in the sample tend to be larger than the published population estimates for this region because of the sampling techniques employed by the Bureau of the Census and the analysis of only multicrop farms.

Applied irrigation water averages 1.45 acre-feet per acre for the study farms. Published estimates for Kansas and Nebraska equal 1.20 acre-feet per acre for the entire population and 1.67 acre-feet-per acre for the 26% of all farms applying greater than 1000 acre-feet.

The study analyzes farms with only groundwater or with a combination of groundwater and surface water. Since groundwater is assumed to be the marginal source, the energy cost of groundwater pumping serves as a proxy for water price. Energy cost for each fuel source is computed from farm-level FRIS data on groundwater pumping depth and pumping pressure using the formula (Gilley and Supalla, 1983, pp. 1785):

$$C = P(1.3716/E)(L + 2.31\mathrm{PSI})$$

where C is groundwater pumping cost in \$/acre-foot, P fuel price, E fuel efficiency, L distance in feet that groundwater must be lifted from the water table, and PSI pumping pressure in pounds per square inch. In the computation, the costs by fuel source (natural gas, LP gas, electricity, diesel, and gasoline) are combined on the basis of farm acres served by each fuel. The sample's average pumping depth is 99 feet and average pumping pressure is 39 psi. The variation in pumping depth and pressure translate into variation in water price. This is important to the econometric analysis of the variable input model of multicrop water allocation. The standard deviations of pumping depth and pressure are 69 feet and 20 psi, respectively, indicating substantial variation.

A complete list of variables for the analysis formed from FRIS is:

WTRPRC

Normalized farm-level energy cost of groundwater pumping ($/acre-foot)

CRPWTR

Water applied to crop i (acre-feet)

TOTWTR

Total water use on farm (acre-feet)

OWNACR

Area devoted to crop i (acres)

TOTACR

Total farm area in crop production (acres)

DMSRWT

Binary variable indicating availability of surface water on the farm (1 if present and 0 otherwise)

DMPRES

Binary variable indicating availability of pressurized irrigation technology (sprinkler or drip) on the farm (1 if present and 0 otherwise)

DMOWNTC

Binary variable indicating availability of pressurized irrigation technology (sprinkler or drip) on crop i (1 if present and 0 otherwise)

DMNOWT

Binary variable indicating the farm discontinued irrigation water use long enough to affect crop yields during the growing season (1 if present and 0 otherwise)

DMLWMG

Binary variable indicating the farm relied on fixed-time water management practices, e.g., water application according to calendar schedule or a water delivery schedule (1 if used and 0 otherwise)

DMHGMG

Binary variable indicating the farm relied on advanced water management practices, e.g., commercial scheduling services, media reports on water use, and/or soil moisture sensing devices (1 if used and 0 otherwise)

Price variables. Since farmers are assumed to make input allocation decisions using expected prices, output price variables for the five crops were predicted using a geometrically distributed lag of state crop price data (USDA, 1985; USDA, 1989) for the five previous years. Output prices were predicted using a non-linear estimation procedure. The wage rate variable was constructed from 1984 state-level and 1988 regional wage data (USDA, 1984; USDA, 1988). Because 1988 data were reported at only the regional level, state-level wage data for 1988 were developed by using ratios of state-level wage data during the period of 1980 to 1984. The price of leaded gasoline purchased in bulk was reported at the regional level (USDA, 1985; USDA, 1989). The bulk gasoline price serves as the numeraire in creating normalized prices:

OWNPRC
Normalized price of crop i
ALFPRC
Normalized alfalfa hay price ($/ton)
BARPRC
Normalized barley price ($/bushel)
CRNPRC
Normalized corn-for-grain price ($/bushel)
DBNPRC
Normalized dry beans price ($/hundredweight)
WHTPRC
Normalized wheat price ($/bushel)
WAGE
Normalized farm labor wage rate ($/hour)

Weather variables. All weather variables are computed from 1988 weather records for cooperative weather stations (Perry, 1990). OWNCDD and OWNPCP are crop-specific continuous variables representing solar energy availability and precipitation available for plant growth. These variables are calculated by summing cooling degree-days and inches of precipitation annually, and averaging the totals across all stations within a given county. Annual totals are customized at the crop level to include only events occurring during the crop's growing season as defined by the Soil Conservation Service's established criteria for that particular crop's water use (USDA, 1967). For example with CRNCDD, total cooling degree-days are held at 0 until the first 2-week period in the year when the water use criterion for corn is met. The variable is then 'switched on', and cooling degree-days are summed. At the end of corn's growing season when the criterion is no longer met, cooling degree-days are 'switched off' with no additional accumulation of CDD:

OWNCDD
Actual base 55 degree cooling degree-days over the growing season of crop i (degree-days)
OWNPCP
Actual precipitation over the growing season of crop i (inches)

Climate variables. Climate variables are based on 1958-1988 average climatic conditions for co-operative stations (Perry, 1988) that are selected to represent county conditions. Climate variables serve as proxies for producer decisions based on long-run expectations of weather patterns but made prior to the observation of the season's weather. The long-run precipitation and cooling degree-day variables represent annual totals, averaged across the 30-year climatic period:

CLMCDD
Long-run average base 55 cooling degree-days (degree-days)
CLMPCP
Long-run average precipitation (inches)

Soil quality variables. All soil quality variables are average county values from the 1982 Natural Resources Inventory conducted by the Soil Conservation Service, USDA (Goebel and Dorsch, 1986). Dummy variables are constructed using NRI land class (scale ranging from 1 to 8) and soil texture information (scale ranging from 1 to 5). GOODSL is positive in areas where land class is rated at 2.25 or less, while BADSL represents areas where land class is rated at 3.5 or more. SAND defines areas where soil texture is rated at 2.5 or less:

SAND
Binary variable representing relatively sandy soil (1 if soil texture is 2.5 or less and 0 otherwise)
GOODSL
Binary variable representing soil with relatively less restrictions that limit use (1 if land class is 2.25 or less and 0 otherwise)
BADSL
Binary variable representing soil with relatively more restrictions that limit use (1 if land class is 3.5 or greater and 0 otherwise)

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